How Do People Perceive Information? Three Essays in Empirical Economics

Dissertation
submitted to the
Faculty of Business, Economics and Informatics
of the University of Zurich

to obtain the degree of
Doktorin der Wirtschaftswissenschaften, Dr. oec.
(corresponds to Doctor of Philosophy, PhD)

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The Faculty of Business, Economics and Informatics of the University of Zurich hereby authorizes the printing of this dissertation, without indicating an opinion of the views expressed in the work.

Zurich, 15.02.2017

The Chairman of the Doctoral Board: Prof. Dr. Steven Ongena

Acknowledgments

First, I would like to thank my advisor, Michelle. Without her support, I probably would not have been able to finish this dissertation. I am deeply grateful for her time, comments, and commitment. It was enriching and rewarding to work with her and I thank her for believing in and encouraging me.

Thanks to my co-supervisor, Uli, who took me under his wing and offered me an office in Oerlikon. I truly appreciate his comments, recommendations, and ideas.

Thanks to my co-authors, Andrew, Steve and Eugenio. It was a great experience to work with these accomplished researchers from different universities. I learnt a lot from their ideas and comments.

Thanks to my dear colleagues and friends, Andràs, Steve, Johannes, Flo, Philippe, Jean-Michel, Lea who accompanied me during this whole process. Thanks also to Michael and le club des escargots.

Thanks to Greg and his group. Thanks to Hannes for his advice and time. Thanks to my other fellow PhD students, to the seminar participants, to the coffee machine.

Thanks to the Excellence Foundation Zurich for giving me a grant to do my PhD work. I am grateful for their support during this journey.

Thanks to my family, my granny, my parents who encouraged me since I was born; and thanks to my sister.

And, last but not least, a particular thanks to Nico who was always there for me, who supported me no matter what, and who cheered me on when it was needed.

Chloé Michel
Zürich, November 2016

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Chapter 1

General Introduction

In everyday life, people are confronted with a large amount of information. The quality and utility of these pieces of information can vary greatly. Some information may deliver useful and even important messages; other information may be nonsense and even be meant to convince people of something untrue. The way people perceive and react to different kinds of information is the focus of this thesis. Do people react the way they should? Do these pieces of information give actual signals or are they just noise? Do they provide people with some utility? The three essays presented here explore how people perceive information that is given to them and how their behaviors and satisfaction with their lives may change after receiving particular pieces of information.

Chapter 2 is concerned with prices presented in stores. In particular, how people react to a pre-promotion price (hereafter, PP price) displayed along with an actual product price. We might assume that consumers only care about the price they pay, as this is what actually matters for their wallet. In practice however, promotions, discounts, and how offers are framed also appear to be important to shoppers. But why does a consumer care about an item's non-discounted price? What does this information convey to her? Price comparisons are mainly offered to influence consumers and uniformed consumers may use these informational signals in forming their perceptions of quality. Once consumers know the product's quality, there is no informative content in the high advertised price. Nevertheless, it may increase consumers' perceptions of savings and directly increase their utility.

To investigate the mechanisms in place and how displayed PP prices may impact shoppers' decisions, I use data on the purchasing behaviors of numerous households in the United States. Comparing informed with uninformed consumers allows me to identify the different effects of PP prices. In the empirical part of this essay, I focus on disposable diaper purchases. Unlike most other products, I am able to observe an individual's initial diaper purchase. People enter the market for diapers because of an exogenous event: the birth of a child. Further, it can be assumed that consumers have no knowledge about the quality of the product before their first purchase. Therefore, by looking at first as well as subsequent purchases, I can identify the informative effect of a non-discounted price for uninformed consumers.

I first run a variety of quantity regressions instrumenting for the price and the PP price. My results show that a high PP price has, in general, a positive impact on the quantity purchased. However, it does not appear to increase the quantity bought at the first purchase by uninformed consumers. To investigate further, I look at purchase probabilities in individual choice models. I find that a high PP price increases the purchase probability of uninformed consumers. This is consistent with the idea that uninformed consumers use the PP price as a signal of quality as this triggers their decisions to buy. Nevertheless, when they are unfamiliar with a product, consumers try it in limited quantities.

This chapter is a first step towards a better understanding of the PP price's effects. Uninformed consumers appear to rely on the hypothesis that price and quality are linked. This idea convinces them to buy an unknown product by relying on, among other characteristics, a higher PP price. Is it the "correct" way to behave? Manufactures and retailers may be tempted to use this strategy and manipulate prices. In particular, they may do so even if the quality-price relationship they present does not reflect the true one.

Chapter 3[1] focuses on how women react to a diagnosis of breast cancer—most probably a life-changing event. Medical treatment is unquestionably the principal component in achieving remission or, ultimately, a cure. However, there is also literature on how lifestyle habits may have an impact on recovery probabilities and, eventually, life expectancy. For example, it has been shown that alcohol consumption is consistently found to be an independent risk factor for breast cancer. Smoking seems to be less clearly related to the risk of developing breast cancer. Further, obesity and weight gain are associated with increased risk for breast cancer (in post-menopausal women), while physical activity may reduce the risk of death from the disease. Numerous agencies spend time and money to investigate the causes of breast cancer and to educate the public. However, little research has been undertaken to examine how risky health behaviors change when a woman receives information about her chances of dying from breast cancer. How do women react to this information? Do they follow the recommendations?

We track a panel of over 9,000 women in the United States over the period 1999 to 2011. These data allow us to observe changes in the women's behaviors; in particular, changes following a breast cancer diagnosis. We develop a model where women make lifestyle choices (how much to smoke, consume alcohol, and engage in physical activity) in each period, and these lifestyle behaviors may be influenced by a breast cancer diagnosis. Estimating random effects ordered probit models we find that whether an individual has been diagnosed with breast cancer has no significant impact on smoking behavior conditional on past behavior and demographic variables. However, women who have had a more recent breast cancer diagnosis (less than five years ago) will significantly decrease their smoking behavior. Further, we find that women do not change their alcohol consumption after a breast cancer diagnosis regardless of when the diagnosis was made. Concerning physical activities, we find

[1] This is a joint project with Michelle Sovinsky and Steven Stern.

that a diagnosis of breast cancer significantly impacts the amount women exercise in a negative direction.

Finally, Chapter 4[2] looks at how a country's advertising expenditures are related to its inhabitants' satisfaction with their lives. Currently, people are confronted with a great deal of advertising. Some billboards and advertisements may be informative; some probably are not. Does all this information have some impact on people's utility and happiness? Looking at advertising expenditures in 27 European countries over more than 30 years, we are able to link these expenditures with the reported life satisfaction of approximately 1 million representative respondents. Running regressions that include the usual control variables (such as age, gender, and macroeconomics) as well as time and country fixed effects, we consistently find a negative link between advertising expenditures made by a country and the inhabitants' reported satisfaction with their lives. This suggests that an overwhelming amount of advertising may not benefit people in their search for happiness. Indeed, this result is consistent with the idea that advertising may stimulate endless desires that deteriorate people's sense of well-being.

While the three chapters of this thesis use different datasets and partially different methodologies, they all seek a better understanding of how people perceive information and how it impacts their behaviors and levels of happiness. The findings in these chapters encourage discussion about the way consumers, patients, and inhabitants react to the information they receive.

[2] This is a joint project with Michelle Sovinsky, Eugenio Proto, and Andrew Oswald.

Chapter 2

What Does This Discount Tell You? Investigating the Impact of Pre-Promotion Price Effects

2.1 Introduction

What does a 50% discount tell buyers? Armstrong and Chen (2013) propose different theoretical models that could explain "why consumers might care about receiving a deliberate discount [...], as opposed simply to obtaining a low price." I consider products that are on promotion and the effects that the pre-promotion price (hereafter, PP price) have on purchase behaviors. I focus on experience goods. A product is considered to be an experience good when its characteristics—such as its quality—are difficult to know in advance but can be determined upon consumption (Nelson, 1970). Consuming a product is, therefore, a way to learn the product's true quality. Other external clues can be used to infer quality when a consumer does not know a product. Advertisements, reviews, and prices of the product are examples of such signals. The underlying idea is that people believe these signals are related to the quality of the product in some way. While using the product gives them a direct signal about its true quality, these other signals provide indirect information about its quality. Depending on the product and the environment, the consumer may need to consume the product many times before knowing its true quality perfectly. In other cases, its quality may be learned after only one trial. Once the product is consumed and its quality revealed, the individual no longer needs quality clues.

Along with a product's actual selling price, retailers frequently display a higher, advertised reference price. These price comparisons are offered to influence consumers who use these informational signals in forming their perceptions of quality. When consumers know the product's quality, these strategies are used to increase consumers' perceptions of savings (Grewal and Compeau, 2007). In this paper, I am specifically interested in the effects of PP prices. While the literature on price effect is vast and multifaceted, discount pricing itself has not received much economic analysis (Armstrong and Chen, 2013). My paper fills a gap by shedding light on the role of the PP price in the context of discounted prices.

In my empirical analysis, I distinguish the different effects of PP prices on consumers' behaviors as well as the underlying mechanisms. To do so, I focus on disposable diaper purchases. Unlike most products, people enter the market for diapers because of an exogenous event—the birth of a child. This provides two advantages: First, I am able to observe an individual's initial purchase; second, the individual can be considered to have no knowledge about the quality of the products offered before this event.[1] I use rich scanner panel data and am able to follow the same individuals making their first and subsequent purchases. Therefore, I have observations from uninformed as well as informed consumers. While the uninformed consumers may use the PP as a signal of quality, the signaling effect disappears once the quality is known. However, even informed consumers may derive some extra utility from getting a good deal. Comparing the price paid with the PP price could increase their utility as it provides them "with a positive transaction value (i.e., a deal)" (Grewal et al., 1998).

In my model, consumers are assumed to know the quality of the product after one trial (one-period learning). I identify the signaling effect of the PP price by looking only at first purchases when the product is on promotion. I am interested to see how this PP price influences the quantity people buy and their buying decisions. To do this, I run different quantity regressions instrumenting for the price and the PP and estimate individual choice models. My results show that the PP price is taken as a signal of quality by uninformed consumers and increases their purchase probability. However, it does not increase the quantity bought the first time. The PP price appears to have a general positive effect in the quantity regression on informed consumers but no clear effect in the individual choice model.

This research is a first step towards a better understanding of the PP price's effects and underlying mechanisms. My findings can be useful for retailers or manufacturers hoping to approach and convince uninformed consumers.

The paper proceeds as follows: Section 2.2 gives an overview of the related literature. Section 2.3 displays a learning model providing an idea of the mechanisms through which signaling and price effects may operate. Section 2.4 presents the dataset used, the patterns that can be found within it, and an explanation of how some variables of interest are constructed. Section 2.5 presents results estimations and, finally, Section 2.6 concludes.

2.2 Literature review

Different theoretical explanations exist to justify why a discounted price—and not simply a low price—can increase a rational consumer's willingness to buy a product

[1] This is particularly true for a person's first child. People who already have one child already have prior experience with diapers. However, that experience can be considered as too old and not pertinent for the current market (Ching et al, 2014).

(Armstrong and Chen, 2013). One explanation is that the original value of a product gives some information about the product's quality. This must be particularly true when consumers use a product for the first time. A vast amount of literature exists about the relationship between price and perceived quality (Rao, 2005). There is less understanding concerning the possible distortion that discounts could cause to this positive price/quality correlation (Palazon and Delgado-Ballester, 2009). Rao and Sattler (2003) mention that price has two distinct roles when consumers evaluate the possible alternatives: the informational role (signal) and the allocative role (constraint). They analyze these effects in an experiment with students by varying the individuals' budget constraints. Their findings show that the informative effect is positive while the allocative effect is negative. However, in their setting they are not able to distinguish whether this is due to a quality effect or a taste for bargains. Mastrobuoni et al. (2014) also use experimental data to disentangle signaling and budgetary effects of price on wine demand. They present a demand model where quality is not perfectly observable and prices have a non-budgetary effect on demand through their signaling value. They find evidence for a signaling effect that appears to be of greater importance to inexperienced consumers. However, their findings rely on hypothetical decisions and not actual purchases.

Most of the literature on price signaling quality focuses on price paid incorporating a signal of quality. However, little is known about the impact of the PP price in the case of discounts. Do people care about the PP price, or solely about the price paid? As mentioned, consumers may use prices to infer unobservable product quality. When an external reference price such as the PP price is present, the price paid may play a lesser role (Panzone, 2014). In their synthesis of research on consumer responses to price, Grewal and Compeau (2007) note that research in the field of advertised price and signals "has not focused on how these cues affect quality perceptions." Darke and Chung (2005) posit that consumers may actually use the lower selling price rather than the original, or PP price, to infer quality.[2] Discounts are often offered for products for which consumers do not have very much information. For example, they are used to sell generic goods, and to introduce a new product or a new brand. In these situations, individuals are more prone to infer some price/quality relationship (Darke and Chung, 2005).

A promotion can give two signals to consumers: The high initial price could increase quality perceptions while the low selling price might decrease them (Darke and Chung, 2005). In a series of small experiments, Darke and Chung (2005) found that discounts give rise to some negative quality inferences especially when people have doubts about a product's quality. Using laboratory experiments on experience goods[3] in the service sector, Raghubir and Corfman (1999) find that, in some particular cases, consumers associate promotions with lower product quality. This is particularly true if the consumers do not have experience with the product. With

[2] In this work, I use the term pre-promotion price—PP price—for the price before any discount. This can also be understood as the original price of a product.

[3] As previously defined, a product is considered to be an experience good when its characteristics are difficult to know in advance, but can be determined upon consumption (Nelson, 1970).

a greater amount of information from other sources, the effect of price on perceived quality will be smaller (Rao and Monroe, 1988). Not every discount has the same impact. For example, Raghubir and Corfman (1999) find from an in-class experiment that a discount offered on a brand name has more effect on consumers' purchase intentions than a similar discount on a store brand. The believability of the advertised retail price has importance. It may well be that "the higher the [advertised reference price], the lower the believability of the offer" (Delvin et al., 2013). This is related to the idea that people may "discount the discounts" (Gupta and Cooper, 1992). All these findings come from lab and web experiments and do not consider actual purchases decisions.

The literature concerned with disentangling the mechanisms of price effects focuses on dynamic learning processes. Consumers learn from price (and possibly other aspects) and update their beliefs about quality (see, for example, Erdem et al., 2008).[4] Learning models make the assumption that individuals have incomplete information about product characteristics. To make their purchase choices, they rely on what they observe: the product's perceived attributes (Ching et al., 2013). Over time, they derive informational cues that help them learn more about products. The information can come through different channels. Trials (or experience) might be the only source of learning. However, external sources can come into play as well, such as advertising, newspapers, promotions, price, reviews, and ratings.

The work of Erdem and Keane (1996) is often viewed as the basis and the unifying framework for subsequent models (Ching et al., 2013). In the Erdem and Keane model (1996), consumers acquire brand quality signals via use experience and advertising. The perceived quality of a brand is a weighted average of individuals' initial beliefs as well as all the quality signals they received previously. Over time, some consumers receive better quality signals than others. The work of Erdem et al. (2008) builds on the Erdem and Keane model (1996) by adding more external signals. In particular, in their model consumers can learn product quality through price, advertising frequency, advertising content, and use experience. For price to be a signal, it is assumed that there is some price/quality relationship. Consumers have prior ideas about mean price and quality and update these beliefs using Bayesian rules. For example, using data on ketchup, they find that price can be considered to be an important quality signal. They posit that people always use the price paid as a signal of quality—even if the product is on promotion. Therefore, frequent price cuts can have a negative impact on brand reputations.

In a similar Bayesian learning framework, Ackerberg (2003) looks at the dual role of advertisements. When consumers have not yet experienced a product, advertising can be directly informative about the product's characteristics. Advertising can also be persuasive and directly impact a consumer's utility without necessarily providing any clear information (Mehta et al., 2008). This persuasive effect occurs even when buyers have full information about the product.

Ching et al. (2014) present a model where learning, inventory, and category

[4] Ching et al. (2013) present a good overview of the literature.

considerations come into play. The learning aspect is similar to Erdem and Keane (1996), in which consumers have uncertainty about product quality and use trials and advertisements as signals to infer quality. Using the category consideration model (developed in Ching et al., 2009), they do not assume that consumers examine prices in every period. Rather, there is a two-stage process: In the first stage, consumers decide whether or not to consider a particular product category. In the second stage—which happens only if they do consider the category—consumers make their choices. In their empirical application to diapers, Ching et al. (2014) find that learning, inventory, and category consideration effects are important and drive consumers' choices. None of these papers on learning models include the possible direct effect of PP price.

Consumers may further display reference dependence preferences (as first proposed by Tversky and Kahneman, 1991). A reference price can be considered as the norm against which people compare and judge the current purchase price of an item (Mazumdar et al., 2005). When the price people must pay is higher than their reference price they may suffer some disutility. When the price presented is lower than their reference point, it could increase their willingness to buy. This is related to the idea that some people are intrinsically attracted to discounts. They obtain direct utility from buying a reduced-priced item. Similar to the transaction utility theory developed by Thaler (1985), the act of making a good deal gives extra utility to the consumer (Grewal and Compeau, 2007). There are, for the most part, two broad reference price concepts (Mazumda et al., 2005): the internal reference price (IRP), which is a memory-based concept; and the external reference price (ERP), which is based on external stimuli. According to Mazumda et al. (2005), the main determinant of a consumer's IRP for frequently purchased packaged goods is the previous price she has observed. Additionally, the more recently the previous purchase occurred, the larger the effect (Mazumda et al., 2005). On the other hand, some people may not rely on past prices but solely consider external stimuli that arise during the purchase occasion. The recommended retail price or the advertised reference price can be considered to be such stimuli.

Mazumdar and Papatla (2000) propose a model where consumers use both an IRP as well as an ERP, but one may be more salient than the other. They emphasize that, usually, there is more than one type of consumer and that the type of product also matters. People tend to use ERP rather than IRP for product categories where promotions are frequent or for those with longer times between purchases. Moreover, the use of an IRP is greater for more costly categories than for cheaper ones. Consumers are, of course, not all the same, and heterogeneity in consumer price responsiveness may also play a role (Bell and Lattin, 2000).

Different theories explain how and why IRP effects arise. Erdem et al. (2010) present a test to differentiate between the two principal versions: price used as a signal of quality and used as a predictor of future prices. Their test is based on variations of how past purchases interact with IRPs. They use data on ketchup and diapers and find that when consumers' experience increases, the reference-price effect decreases. Consumers in their setting do not derive any extra utility from the fact that a product is discounted.

In my empirical analysis, I focus on diaper purchases. The market for diapers and its consumers have particular features of note. Demand for diapers is stable and, to a great extent, not related to macroeconomic conditions (Haucap et al, 2013). Since parents buy diapers often, a relatively large number of purchases can be observed (Ching et al., 2014). They appear to be quality-sensitive customers and care about the quality of the product (Haucap et al, 2013). In this category, a consumer begins buying due to an exogenous event, namely the birth of a child. In most other product categories —for example, the laundry detergent or cereal category—consumers have been in the market for a long time (Ching et al., 2014) and it is, therefore, difficult to observe a first purchase.

As explained, the literature on the price effect is vast and multifaceted. However, discount pricing itself has not received much economic analysis (Armstrong and Chen, 2013). In the context of discounted price, my paper fills a gap in the literature by shedding light on the role of the PP price by looking at its effect and understanding why people react as they do.

2.3 Theory Model

In this section, I present a learning model to motivate the mechanisms through which price effects might operate. The learning process relies on Bayesian updating. However, as has been noted in the literature, "sizable empirical evidence documents systematic violations of" updating based on Bayes' rule (Ortoleva, 2012). Nevertheless, this framework remains a good way to introduce my identification strategy and to understand the mechanisms that may play a role. A more general model with various details can be found in Appendix 2.6.

Consumer i does her shopping in period t and faces products $j = 1, ..., J$. The price paid is denoted p_{ijt}. The discount (if any) is denoted by d_{it} and the price without discount—the PP price—is denoted by P_{ijt}. Thus $P_{ijt} = p_{ijt} + d_{ijt}$. If there is no discount, the price paid is equal to the PP price. This PP price serves as a signal of quality for consumers[5] and they use it when making inferences about quality.[6] The good considered is an experience good and is assumed to be nondurable enough that it is consumed/used before the next purchase (as in Ackerberg, 2003). In a given period, consumers observe prices of all the products available, as well as the corresponding discounts, and decide to purchase one of the products or the outside alternative.

Following Erdem et al. (2008), I assume the following form for the utility function:

$$U_{ijt} = \alpha_i p_{ijt} + \beta_i Q_{ijt}^E + \beta_i r_i \left(Q_{ijt}^E\right)^2 + \gamma_i d_{ijt} + e_{ijt}, \tag{2.1}$$

[5]This is not like Erdem et al., 2008 who assume that the price signal always comes from the price paid.

[6]That is, when a product is presented as "50USD instead of 100USD", it is assumed that people use 100USD to infer quality rather than 50USD.

where p_{ijt} is the price paid by the consumer for this product, Q^E_{ijt} is the "experience quality" (Erdem et al., 2008) or "experience utility" (Ackerberg, 2003), r_i represents the consumer's risk aversion towards variations in quality, d_{ijt} is the discount (if any), and e_{ijt} is a taste shock known to the consumer but not to the econometrician.

Experience quality, Q^E_{ijt}, is the measure of the utility that consumer derives from product characteristics that are not directly observable to her. It is not known before the purchase and the Q^E_{ijt} might, for example, represent the length of time before the first leak from the diaper. Once the good is purchased and used, Q^E_{ijt} is revealed. The simplest case is the one-period learning process where Q^E_{ijt} is constant for all future periods. After one purchase, the consumer knows the experience utility for all future t. The general way of writing the learning process is

$$Q^E_{ijt} = Q_j + \xi_{ijt} \text{ where } \xi_{ijt} \sim N(0, \sigma^2_\xi).$$

Q_j is the true quality of the product, but consumers do not experience it directly as a user's experience is context dependent (Erdem et al., 2008). The ξ_{ijt} are referred to as the experience variabilities and are not distinguishable from the mean.

Before any experience in the market, at $t = 0$, individuals have some prior beliefs about the mean prices and the mean experience quality level of products. Over time, the use experience gives households signals about quality (Erdem and Keane, 1996). In addition, people use the price as a signal of quality. It is assumed that the PP prices observed by the consumers, P_{ijt}, follow the process

$$P_{ijt} = P_j + \omega_{ijt}, \quad \omega_{ijt} \sim N(0, \sigma^2_\omega), \tag{2.2}$$

where P_j is the mean PP price. Deviations around the mean P_j exist because some consumers may not see the PP price posted during a promotion, or there may be some variation in where and when the PP price is posted. Consumers believe that this mean price is related to the product quality as follows (Erdem et al., 2008)

$$P_j = \phi_0 + \phi_1 Q_j + \eta_j, \tag{2.3}$$

where Q_j is the product's "true" quality and consumers perceive that the η_j are distributed according to $\eta_j \sim N(0, \sigma^2_\eta)$. Consumers use the observed P_{ijt} to learn about P_j.

Both signals—use experience and PP price—impact the perceived quality of the product. The whole process can be written as a combination of initial priors at $t = 0$, the learning process, and consumer's updated beliefs about the product j after a history of observed PP prices and use experiences (Ackerberg, 2003; DeGroot, 1970).[7] The consumer derives information on true brand quality Q_j through PP price, as well as usage. However, while buying and using the product gives direct information on Q_j, the PP price only provides indirect information through the consumer's prior beliefs that PP price and true quality are correlated (equation (2.3)). The more

[7] Details to the formulas can be found in 2.6.

direct information the consumer gains via using the product, the less she needs indirect information through the PP price. Therefore, all else being equal, the more usage experience an individual has, the less information will be in the PP price signal and the less it will impact her expected utility function.

In a one-usage learning model (where true quality is learned after only one use), the PP price will have no impact on a consumer after she has bought and used the product once (Ackerberg, 2003). However, the PP price may impact a consumer directly via the discount, $\gamma_i d_{ijt}$, as seen in equation (2.1). While the signaling effect of the PP price solely impacts uninformed consumers, the direct effect of a high PP price also impacts persons with experience.

2.4 Data

2.4.1 Description of the Dataset

I use data from the Nielsen Company, provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business.[8] The data are for the years 2011, 2012, and 2013 and the markets of Chicago and Atlanta in the United States. Both a consumer panel dataset and a retailer scanner dataset are available. The consumer panel dataset is a longitudinal survey with annual updates. Panelists use in-home scanners to record their purchases from any outlet. The retailers are from any US market, and panelists are geographically dispersed. The dataset contains information about price and product characteristics as well as other purchase information for a large number of food and non-food items. The retail scanner dataset contains weekly prices as well as volume and merchandising conditions from participating retail stores in the markets.

Following the literature on learning models, I focus on disposable diapers.[9] In this product category, quality is an important factor—no one wants to experiment with leaking diapers—and people care about the objective attributes of the product. As mentioned in Erdem et al. (2010), diapers are a good example of a product for which price plays a relevant role as a signal of quality. The usage cycle of diapers is also shorter than for other quasi-durable goods (Ching et al, 2014) and this provides more observations. Moreover, as noted in Kumar and Leone (1988), "stockpiling of this product is uncommon because of the high price and general bulkiness of the box." Diapers are also considered to be in the low stockpiling category by Bronnenberg et al. (2008). Another advantage of diapers for my study is that people usually start buying diapers only after they have children. This is an exogenous event and, therefore, the initial purchase (which is often missing for other product categories) can be observed (Ching et al., 2010). Further, this category is dominated by four leading brands (Erdem et al., 2010; Ching et al., 2014): Pampers, Huggies, LUVS, and the generic

[8] For information on availability and access to the data, see http://research.chicagobooth.edu/nielsen.

[9] I restrict the data to diapers, drop training pants, and other underwear for older children.

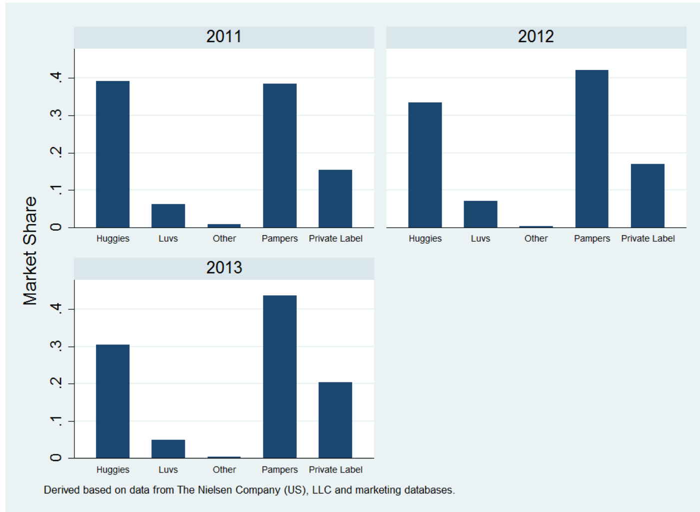

Figure 2.1: Market Shares of the Four Leading Brands and the "Other" Brand, by Year

store brands (labeled "Generic" or "Private Label Brand"). Figure 2.1 illustrates the market shares of the four leading brands in the three years considered.

My initial sample consists of 827 households who buy diapers and have children. Several households must be dropped from the analysis based on their purchasing profiles. First, I exclude households that make three or fewer purchases over the sample period (548 households dropped). This exclusion is necessary to have enough data points for the individual choice model. It is important to have observations on purchases made with and without experience to identify the different effects. Further, I drop households that make between four and seven purchase trips and include no children under 6 years old (65 households dropped). This exclusion is specific to the diaper category and is made because it seems that these people are buying diapers for others (Erdem et al., 2010).[10] In addition, concerning the choices made, I drop observations from households who do not buy diapers from the four main brands. Similarly, I exclude the purchase observations when a household chooses multiple brands during one shopping trip (Erdem et al., 2010).[11] My final sample consists of 214 households who choose at most one brand at each purchase occasion. On average, I observe 13.7 diaper purchases per household, which leads to a total of 2938 purchases observed.

My unit of observation is defined at the week t level. There are few households that make more than one purchase during one week. For these, I aggregate their multiple purchases into one single purchase.

[10]They could be grandparents or other relatives who intermittently buy diapers for the child's parents or to have at home for when the child visits. As they do not regularly live with the child (no children under 6 live in their households), they do not have a true experience with the product's quality.

[11]A household may buy different products, but they are mostly from the same brand. Less than 6% of the observations come from multiple brands purchased during one trip.

I identify households making their first purchase in the diaper market as those who took a long time before making a purchase in the time period (Erdem et al., 2010) and then purchase regularly. In particular, a household's purchase at time t_1 is considered to be the first ever if

$$t_1 > \max_{j=1,\ldots,N-1} \{t_{j+1} - t_j\},$$

where $N-1$ is the second-to-last period in the sample. This means that "the first inter-purchase spell is longer than any subsequent inter-purchase spell" (Ching et al. 2014). The first inter-purchase spell is calculated with respect to the start of my sample: January 1, 2011. However, I may miss new parents who buy for the first time at the beginning of 2011 and for which the first spell is automatically small. To avoid that, I also consider a household as a first buyer if this household was present in the panelists of 2010 but did not buy any diapers in that year (i.e., their first purchase of diapers is in 2011).[12] For 44% of my observations, the first diaper purchase takes place during the sample period. Table 2.1 presents the summary statistics of my

Table 2.1: Summary Statistics for my Sample

Variable	Mean	Std. Dev.
Live in Chicago	0.654	0.476
Ethnicity of the Household		
Caucasian	0.652	0.477
African American	0.196	0.397
Other	0.153	0.36
Composition of the Household		
Size of the Household	3.622	1.407
Number of Children	1.456	1.287
Married Couple	0.879	0.326
Highest Education Grade		
Grade School	0.006	0.075
High School	0.267	0.443
College	0.477	0.500
Post College	0.250	0.433
Earnings		
Total Income < \$30,000	0.072	0.258
\$30,000 ≤ Total Income < \$50,000	0.159	0.366
\$50,000 ≤ Total Income < \$100,000	0.458	0.498
Total Income ≥ \$100,000	0.311	0.463
Number of Household-Week	**2270**	
Age of the Female		
Under 40	0.562	0.496
Between 40 and 49	0.256	0.437
50 and Older	0.182	0.386
Number of Household-Week	**2234**	
Age of the Male		
Under 40	0.457	0.498
Between 40 and 49	0.335	0.472
50 and Older	0.208	0.406
Number of Household-Week	**2053**	

Notes: Children are defined as being younger than 18 years old.
Calculations are based on data from The Nielsen Company (US), LLC and marketing databases.

sample. As it can be seen, the majority of the households are located in the Chicago

[12] People who have multiple children with a long gap between each of them could also be considered as first buyers with this definition. These households are, therefore, not making their very first purchase. However, their past experience can be considered as too old to be really relevant in the current market (Ching et al. 2014).

area (65%) and are Caucasian (65%). On average, a household consists of a married couple (88%) and of 1 to 2 children (1.5). The ages of the female and male heads are reported in the bottom panel of Table 2.1. For both categories, it can be seen that the largest group of respondents are people younger than 40 years old.

The price of a product is an important characteristic. Not only the price paid by a consumer, but also past prices as well as prices a consumer sees when she goes to the store, even if she does not buy anything. In an ideal world, I would have sufficient information about each specific product and each price in each period. However, this is not the case. The consumer dataset only contains prices (and product characteristics) for actual purchases by panelists. I can rely on the retail dataset to complete some price information but there are two main caveats. First, the retail dataset only covers a subsample of the stores; second, every detail is masked (for privacy reasons) for products from a generic store brand. These products only can be matched imperfectly with the consumer panel dataset. As mentioned above, the private brand represents a non-negligible part of the disposable diaper industry.

It is not possible to construct an exact price history for each Universal Product Code (UPC). Therefore, I follow the literature and focus on brand choices (Mayhew and Winer, 1992, Erdem et al., 2008, Erdem et al., 2010). For diapers, as noted in Erdem et al. (2010) and Ching et al. (2014), this is not trivial because each brand offers a large number of different product sizes and package sizes. I define my product as a brand /diaper size combination for each store. I first aggregate each brand's diaper sizes into four different categories, from diapers for newborns to diapers for infants weighing more than 15kg. A price index is constructed for each "diaper size×brand×store×week" (as in Erdem et al, 2010).

This price index is designed by using a weighted average of prices for different package sizes. These weights reflect the relative quantity sold of each package size. For example, consider diaper size 3. For this diaper category, let us say that Pampers offers four different package sizes. Each of these package sizes sells a specific amount and this corresponds to a certain market share (in quantity terms) within the brand (calculated by city and for the entire sample length), say $\frac{1}{2}$, $\frac{1}{10}$, $\frac{1}{5}$ and $\frac{1}{5}$. I first calculate a simple average price for each of these four package sizes in each store week (denoted $\overline{p}_1$, $\overline{p}_2$, $\overline{p}_3$ and $\overline{p}_4$). The Pampers' price index for a specific diaper size, in a specific store, in a specific city, will be a share weighted average of these mean prices, that is $\frac{1}{2}\overline{p}_1 + \frac{1}{10}\overline{p}_2 + \frac{1}{5}\overline{p}_3 + \frac{1}{5}\overline{p}_4$.[13]

There is a total of 1,710 different "store×brand×diaper size" combinations for 156 weeks, which corresponds to a total of 266,760 observations. A relatively large part of these observations are missing. For them, I follow the literature (Erdem et al. 2010, Ching et al. 2014) and replace the price index by average prices offered in the same market (Chicago or Atlanta) for the same "diaper size×brand".[14] For the

[13] In practice, this is slightly more subtle because not every store sells all existing package sizes every week. Thus, I use the weights but corrected for whether I have information for this store for this package in this week.

[14] At first, 85% of the 266,760 observations are missing. After filling the prices with market prices, 42,605 (16%) observations are still missing.

remaining missing values, I extrapolate the price index from $t-1$ and $t+1$. If both price indexes are available, I use an average of both; if only one is available, I use that one.[15]

In order to use the price index in the consumer choice decision, I transform it into a unit price index. Therefore, I do not consider quantity discounts. In my sample, I have data on an average of 2.4 different products by store.[16]

Figure 2.2 presents the average unit price index for all four brands by diaper size. It shows that Pampers and Huggies have a higher average price index, while the private label and LUVS are the cheapest brands.

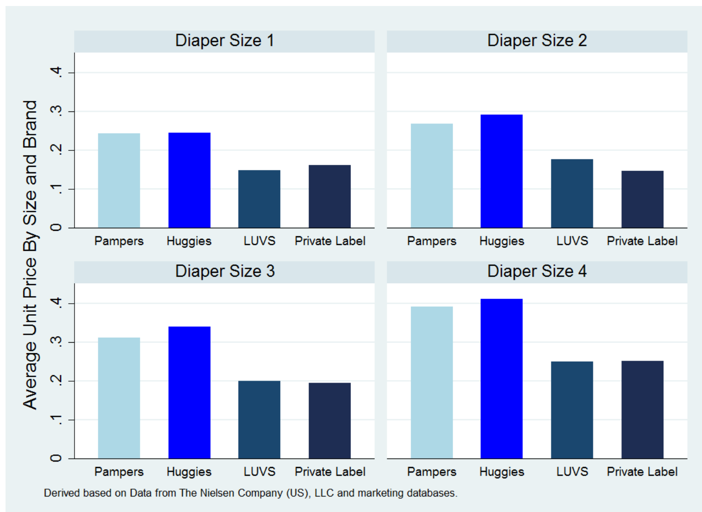

Figure 2.2: Unit Price Index by Diaper Size and Brand

The data do not contain one general indicator of temporary price reductions. In the consumer panel data, there is a "perceived as a deal" variable but this is unfortunately not enough for the whole price index process. Following Nielsen's recommendation and the literature, I define a price reduction by comparing actual prices to historical prices. In particular, I define a "sale as any price at least 5 percent below the modal price" (Hendel and Nevo, 2006). Figure 2.3 shows this indicator for a particular brand.

Table 2.2 presents some descriptive statistics of the unit price averaged by diaper size for each brand. As expected, the private label has, overall, the lowest unit price index while Huggies is the most expensive brand.

[15] Twenty-five percent of the missing values could be filled with this extrapolation. For the rest (where no prices were available either in $t+1$ or in $t-1$), I look at the two periods prior and use these price indexes.

[16] The number of products by store ranges from one to 14.

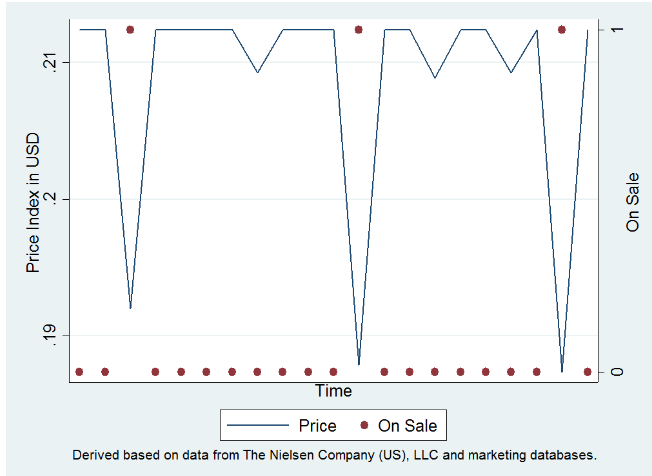

Figure 2.3: Price Index and “On Sale” Indicator

Table 2.2: Descriptive Statistics

Brand	Market Share	Unit Price Index	Promotion Frequency
Pamper	0.337	0.290	0.166
Huggies	0.303	0.320	0.143
Luvs	0.062	0.193	0.272
Private Label	0.298	0.183	0.344

Calculations based on data from The Nielsen Company (US), LLC and marketing databases.

2.4.2 Preliminary Analysis

Figure 2.4 shows that there is variation in household purchase decisions. In this example, household 1 appears to only choose the private label brand while household 2 switches between brands. Figure 2.5 shows three households with different purchase preferences. Household 1 purchases diapers at a non-discounted price, household 2 almost solely buys diapers that are on sale, while household 3 appears to like both.[17]

Table 2.3 presents mean statistics for consumers who are newer to the market (for whom I observe their first purchase) as well as for those who have been present in the market for a longer time, facing a price on promotion or not. The size of the household is larger for experienced consumers, which makes sense as some of them have more than one child. New consumers appear to be poorer than experienced consumers. When the price is on promotion, new consumers more often choose Pampers, while experienced consumers buy Huggies the majority of the time. The private label brand is chosen most of the time when there is no promotion.

[17] For each of these three households I have more than 20 observations points.

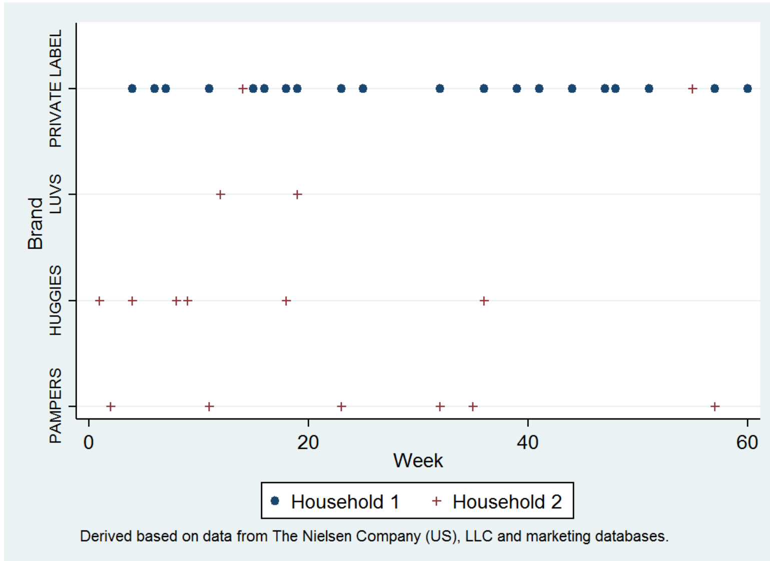

Figure 2.4: Comparison of Brand Choices for Two Households

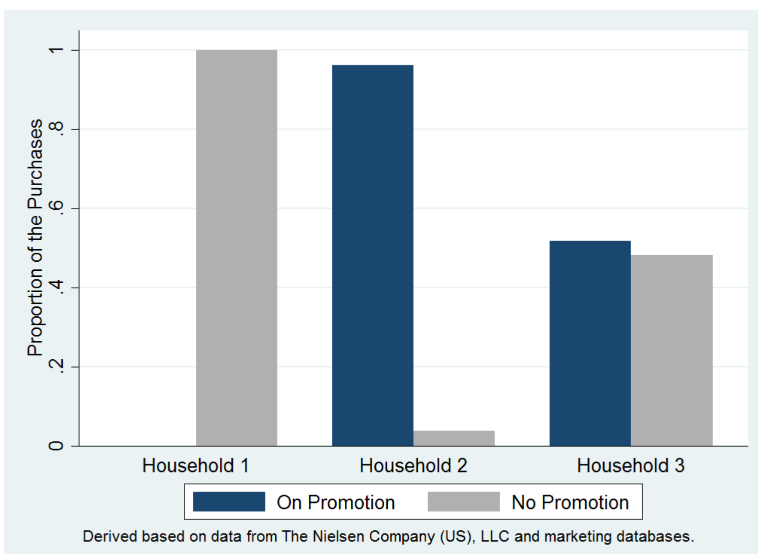

Figure 2.5: Comparison of Purchases when Price is on Promotion or Not for Three Households

Table 2.3: Experimented and Less Experimented Consumers Facing Prices on Promotion or Not

	Less Experimented Consumers		Experimented Consumers	
	Promotion	No Promotion	Promotion	No Promotion
Ethnicity of the Household				
Caucasian	0.69	0.63	0.65	0.65
African American	0.13	0.32	0.21	0.15
Other	0.18	0.05	0.15	0.21
Composition of the Household				
Size of the Household	3.47	3.30	3.69	3.82
Married Couple	0.84	0.83	0.91	0.85
Earnings				
Total Income $<$ \$30,000	0.12	0.07	0.03	0.09
\$30,000 $\leq$ Total Income $<$ \$50,000	0.20	0.31	0.09	0.13
\$50,000 $\leq$ Total Income $<$ \$100,000	0.45	0.37	0.51	0.45
Total Income $\geq$ \$100,000	0.23	0.25	0.37	0.34
Age of the Female				
Under 40	0.61	0.51	0.55	0.58
Between 40 and 49	0.17	0.26	0.34	0.22
50 and Older	0.21	0.23	0.11	0.20
Age of the Male				
Under 40	0.52	0.33	0.49	0.47
Between 40 and 49	0.25	0.38	0.38	0.32
50 and Older	0.23	0.30	0.13	0.21
Size of the Diapers				
Size 1	0.19	0.21	0.12	0.13
Size 2	0.22	0.29	0.20	0.19
Size 3	0.31	0.25	0.40	0.35
Size 4	0.27	0.25	0.28	0.32
Chosen Brand				
Pampers	0.42	0.27	0.35	0.25
Huggies	0.35	0.25	0.48	0.22
LUVS	0.05	0.11	0.05	0.11
Private Label	0.17	0.36	0.13	0.41
Number of Household-Week	484	516	686	584

Calculations based on data from The Nielsen Company (US), LLC and marketing databases.

2.4.3 Identification Strategy

Discounted prices have different effects on consumers' purchase behaviors. In particular, three different price effects can occur simultaneously or separately. First, the price paid by consumers has an effect on the quantity they buy and on the buyers' utility. Second, when a product is on promotion, consumers may use the PP price as a signal of quality. This will happen most often for consumers who are not familiar with the brand (Darke and Chung, 2005). Uninformed consumers facing a product not on sale may similarly use the price paid as a signal of quality. Third, when the price of a product is discounted, consumers can also derive extra utility directly. It has been shown that promotions can increase consumers' perceptions of the offer value. This is related to the transaction utility (Thaler, 1975) and the idea that discounts augment buyers' utility beyond the economic consequences (Darke and Chung, 2005). The usual price effect is present in all situations, no matter how informed consumers are. In this work, I focus on the signaling effect of the PP price. By definition, this effect only happens when the price is on promotion. Further, it is only present when people are uninformed about the product. By comparing a first purchase with subsequent purchases when the product is on promotion, I am able to disentangle the bargaining effect from the signaling effect. Looking at informed consumers facing no promotion, allows me to identify the usual price effect.

Table 2.4 summarizes the different effects disaggregated by consumer type and promotion status. Price can be discounted or not, and consumers can be informed about the brand or not. In Table 2.4, uninformed consumers could learn about the product's quality via the price paid if there is no promotion. Once a consumer is an informed user, she no longer needs quality signals and this effect disappears. When products are on promotion, these price cuts may impact consumers' utility and behavior directly. It does not matter whether or not they are informed.

Table 2.4: Indentification Strategy

	Price	
Consumers	With Discount	No Discount
Uninformed	Quality Signal[1] Price Effect Bargain	Quality Signal[2] Price Effect
Informed	Price Effect Bargain	Price Effect

[1] from the pre-promotion price, [2] from the price paid

Therefore, comparing uninformed consumers and informed consumers when there is no discount allows me to isolate the quality signal of the price paid. Comparing uninformed consumers and informed consumers when there is a discount allows me to identify the quality signal of the PP price. Finally, comparing informed consumers when there is a discount with informed consumers when there is no discount allows me to identify the bargaining effect of the discount.

2.5 Empirics

In Section 2.3, I provided a theoretical learning model to understand the mechanisms through which price effects may operate. In this section, I present details on the models that are estimated as well as the results. I first look at quantity regressions and then at a structural individual choice model.

2.5.1 Quantity Regressions

The first equation of interest is of the form:

$$\ln(Q_{ijt}) = \beta_0 + \beta_1 \ln(p_{ijt}) + \beta_2 \ln(P_{ijt}) \times S_{ijt} + \beta_3^T X_{it} + \beta_4^T Y_{jt} + \varepsilon_{ijt}, \tag{2.4}$$

where Q_{ijt} is the quantity of product j bought by household i at time t —defined as the number of packages multiplied by the number of diapers in the package, , p_{ijt} price per diaper of product j offered to a consumer i at time t, P_{ijt} is the pre-promotion (PP) price per diaper of product j offered to consumer i at time t, S_{ijt} is an indicator equal to 1 if $P_{ijt} \neq p_{ijt}$ (i.e., there is a discount) when household i buys product j at time t, X_{it} are demographics of the household, and Y_{jt} are product characteristics. The product is defined as a “brand-diaper size” combination. Further, X_{it} contains the size of the household, whether this is the first purchase or the purchase frequency, ethnicity, and income of the household. Y_{jt} contains a brand indicator and a diaper size indicator. I also include city, retailer, year, and month fixed effects. These fixed effects are included because unobserved events can happen during one year, one month or at one retailer that may have a general impact on demand. As I cannot entirely observe them, I control for them by including fixed effects. At each t (week), a consumer i can buy at most one “brand-diaper size” combination.

I start by running regressions including only the price paid. Various OLS regressions are presented in columns (1) to (4) of Table 2.5. As expected, the price (per unit) has a negative impact on the quantity purchased but this effect is not very strong. It is, of course, unrealistic to think that price is exogenous and the correlation between prices and demand shocks are included in the econometric error term. An instrument that is directly correlated with the price but not directly with the demand is needed. Following Hausman (1996) and Nevo (2001), I use the price of the same product in all other available markets (from the total scanner panel) as an instrument. The justification for such an instrument is that city-specific demand shocks are independent across cities. A demand shock for a particular brand will then not be correlated with prices of the same brand in other cities. Due to common marginal cost shocks, prices of a brand in different cities are, however, not independent of each other (Nevo, 2001). Columns (5) to (9) of Table 2.5 present instrumental variable regressions. The price coefficient becomes more negative, which is what was expected.[18] The first stage F-test is large, which indicates that the instrument is not weak.

[18] As the regressions presented are log-log regressions, the coefficients of the price coefficient can

To proxy for inventory effect, I add some dummy variables indicating the time spent since the last purchase of a household. Four categories are included: first purchase (that is, there is no inter-purchase time), two weeks or less, three to four weeks, and five to six weeks. The omitted category is more than 6 weeks. In the OLS regressions, the dummies are partially significant and have the expected sign. The longer the time since last purchase, the more the consumer buys (the coefficient is less negative). In the IV regressions however, none of the dummies is significant.

My variable of interest is the PP price—the P_{ijt} as mentioned in equation (2.4))—and, thus, I include it in the next set of regressions. Table 2.6 presents OLS and IV regressions with the price paid as well as the PP price as regressors. I again instrument the price paid with the price from the other markets. The PP price is probably endogenous as well. To instrument for it, I use characteristics of rivals' products as proposed by Berry et al. (1995). In my setting, I consider how often other products (other disposable diapers, brands, size combinations) at the same store are on promotion. The idea is that characteristics of a specific product will depend on how closely substitutable this product is with the other offered products. However, characteristics of other rival products should not affect consumers' valuation of a specific product. It can be seen that the price coefficient remains negative and the values are similar to the ones in Table 2.5. The PP price appears to have a positive effect on the quantity bought. This effect is stable even when I include year, retailer, and month fixed effects.

Table 2.7 shows two instrument regressions for informed and less informed consumers. Column (1) presents regressions for people for whom I have information on their first purchase. They are, therefore, relatively new to the market and less informed than the informed consumers in column (2). These latter consumers have been in the market longer and have better information on the products and brands offered. The mean price elasticity is lower for the less informed consumers. This is consistent with what has been found in the literature; namely, that new parents are less elastic because of time constraints and lack of information (Calzolari et al., 2012). The variable of interest is the coefficient on the PP price. It is significant and positive in both columns. These two coefficients do not necessarily capture the same thing. While the coefficient in column (1) may capture the informative effect of the PP price, the coefficient in column (2) may be related to the fact that people like bargains.

I further try to disentangle the PP price effect for inexperienced consumers. My underlying assumption here is that once an individual has tried a brand, she knows its quality and thus the signaling effect should not come into play.[19] Table 2.8 presents results for individuals for whom I have information on their very first purchase. I add an interaction term between the (log of) unit price paid, the (log of) unit PP

be considered as mean elasticities. The values I find are very similar to the ones found in Rickert (2016).

[19] It could be that consumers need more than one purchase to totally learn the quality of a product. If this is the case, the signaling effect of the PP price found can be considered as a lower bound of the total signaling effect.

Table 2.5: OLS and IV Regressions, Unit Price Paid

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV	(6) IV	(7) IV	(8) IV
Unit Price Paid	-0.237***	-0.239***	-0.247***	-0.248***	-3.663***	-3.730***	-2.431***	-2.544***
	(0.068)	(0.068)	(0.055)	(0.055)	(0.473)	(0.482)	(0.271)	(0.291)
Brand								
Pampers	0.311***	0.313***	0.183***	0.180***	1.489***	1.519***	0.904***	0.935***
	(0.045)	(0.045)	(0.040)	(0.040)	(0.150)	(0.153)	(0.104)	(0.111)
Huggies	0.108*	0.111**	-0.025	-0.025	1.091***	1.129***	0.605***	0.644***
	(0.042)	(0.042)	(0.037)	(0.037)	(0.128)	(0.132)	(0.092)	(0.098)
LUVS	0.094	0.091	0.039	0.034	0.346***	0.364***	0.123*	0.131*
	(0.053)	(0.053)	(0.053)	(0.053)	(0.071)	(0.074)	(0.062)	(0.064)
Diaper Size								
Size 1-2	0.147**	0.142**	0.111*	0.110*	-1.465***	-1.492***	-0.940***	-0.991***
	(0.055)	(0.055)	(0.046)	(0.047)	(0.238)	(0.241)	(0.141)	(0.149)
Size 3	0.251***	0.253***	0.283***	0.283***	-1.123***	-1.137***	-0.602***	-0.647***
	(0.046)	(0.046)	(0.041)	(0.041)	(0.190)	(0.193)	(0.117)	(0.124)
Size 4	0.086*	0.090*	0.142***	0.142***	-0.736***	-0.729***	-0.339***	-0.364***
	(0.039)	(0.039)	(0.035)	(0.035)	(0.126)	(0.127)	(0.079)	(0.084)
Household Demographics								
Chicago	0.328***	0.327***			0.258***	0.248***	0.134*	0.133*
	(0.031)	(0.031)			(0.060)	(0.059)	(0.055)	(0.056)
Size of the Household	-0.041***	-0.039***	-0.016	-0.016	-0.092***	-0.089***	-0.063***	-0.065***
	(0.011)	(0.010)	(0.009)	(0.010)	(0.025)	(0.025)	(0.017)	(0.018)
White	0.009	0.011	0.039	0.038	-0.101	-0.101	-0.012	-0.018
	(0.030)	(0.030)	(0.026)	(0.027)	(0.059)	(0.060)	(0.041)	(0.042)
Income $\leq$ 30,000USD	-0.458***	-0.446***	-0.167**	-0.172**	-0.617***	-0.605***	-0.280***	-0.289***
	(0.058)	(0.058)	(0.056)	(0.056)	(0.109)	(0.110)	(0.082)	(0.084)
30,000 $\leq$ Income $<$49,999USD	-0.209***	-0.219***	-0.098*	-0.0987*	-0.223**	-0.243**	-0.108	-0.107
	(0.042)	(0.042)	(0.039)	(0.039)	(0.075)	(0.077)	(0.059)	(0.060)
50,000 $\leq$ Income $<$99,999USD	-0.072*	-0.069*	-0.0027	-0.003	-0.284***	-0.287***	-0.148**	-0.156**
	(0.034)	(0.034)	(0.029)	(0.029)	(0.068)	(0.0688)	(0.047)	(0.048)
Time Since Last Purchase								
First Diaper Purchase	-0.144*	-0.146*	-0.071	-0.074	-0.178	-0.177	-0.074	-0.074
	(0.071)	(0.071)	(0.062)	(0.063)	(0.170)	(0.172)	(0.118)	(0.126)
Two weeks or less	-0.178***	-0.171***	-0.108**	-0.110***	-0.148*	-0.135	-0.076	-0.079
	(0.038)	(0.038)	(0.033)	(0.033)	(0.072)	(0.073)	(0.049)	(0.051)
Three or four weeks	-0.122***	-0.117**	-0.023	-0.026	-0.069	-0.059	-0.002	-0.010
	(0.037)	(0.037)	(0.032)	(0.032)	(0.073)	(0.074)	(0.051)	(0.052)
Five or six weeks	-0.017	-0.020	0.017	0.011	-0.006	-0.004	0.021	0.006
	(0.044)	(0.044)	(0.037)	(0.037)	(0.082)	(0.082)	(0.055)	(0.057)
Fixed Effects								
Year	no	yes	yes	yes	no	yes	yes	yes
Retailer	no	no	yes	yes	no	no	yes	yes
Month	no	no	no	yes	no	no	no	yes
Constant	3.881***	3.840***	3.730***	3.673***	-0.796	-1.034	0.841*	0.558
	(0.117)	(0.120)	(0.109)	(0.133)	(0.640)	(0.663)	(0.370)	(0.418)
N	2252	2252	2252	2252	2244	2244	2244	2244
adj. R^2	0.163	0.166	0.409	0.408				
First Stage F-test					99.80	98.00	128.89	115.32

Robust standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Calculations based on data from The Nielsen Company (US), LLC and marketing databases.

Table 2.6: OLS and IV Regressions, Unit Price Paid and Unit Pre Promotion Price

	(1) OLS	(2) OLS	(3) OLS	(4) OLS	(5) IV	(6) IV	(7) IV	(8) IV
Prices								
Unit Price Paid	-0.258***	-0.259***	-0.235***	-0.236***	-3.353***	-3.386***	-2.511***	-2.619***
	(0.073)	(0.073)	(0.057)	(0.057)	(0.427)	(0.430)	(0.286)	(0.306)
Unit PP Price	0.036	0.034	-0.022	-0.022	0.879***	0.885***	0.484***	0.508***
	(0.025)	(0.025)	(0.023)	(0.023)	(0.149)	(0.149)	(0.110)	(0.114)
Brand								
Pampers	0.334***	0.335***	0.171***	0.168***	1.752***	1.770***	1.113***	1.152***
	(0.050)	(0.050)	(0.043)	(0.044)	(0.173)	(0.173)	(0.131)	(0.138)
Huggies	0.132**	0.133**	-0.039	-0.038	1.422***	1.448***	0.853***	0.898***
	(0.047)	(0.047)	(0.040)	(0.041)	(0.159)	(0.162)	(0.124)	(0.131)
LUVS	0.100	0.098	0.035	0.030	0.411***	0.424***	0.188**	0.199**
	(0.054)	(0.053)	(0.054)	(0.054)	(0.082)	(0.084)	(0.069)	(0.071)
Diaper Size								
Size 1-2	0.139*	0.135*	0.115*	0.113*	-1.255***	-1.267***	-0.919***	-0.962***
	(0.057)	(0.056)	(0.047)	(0.047)	(0.209)	(0.210)	(0.146)	(0.154)
Size 3	0.246***	0.248***	0.285***	0.285***	-0.914***	-0.919***	-0.561***	-0.599***
	(0.047)	(0.047)	(0.041)	(0.041)	(0.161)	(0.162)	(0.120)	(0.126)
Size 4	0.087*	0.091*	0.141***	0.142***	-0.507***	-0.500***	-0.273***	-0.289***
	(0.039)	(0.039)	(0.035)	(0.035)	(0.106)	(0.106)	(0.083)	(0.087)
Household Demographics								
Chicago	0.324***	0.323***			0.184**	0.175**	0.130*	0.133*
	(0.031)	(0.031)			(0.057)	(0.057)	(0.057)	(0.058)
Size of the Household	-0.040***	-0.039***	-0.016	-0.016	-0.082***	-0.080***	-0.068***	-0.069***
	(0.010)	(0.010)	(0.009)	(0.010)	(0.022)	(0.023)	(0.018)	(0.019)
White	0.011	0.012	0.038	0.037	-0.042	-0.042	0.023	0.018
	(0.030)	(0.030)	(0.027)	(0.027)	(0.056)	(0.056)	(0.042)	(0.044)
Income $\leq$ 30,000USD	-0.456***	-0.444***	-0.168**	-0.173**	-0.567***	-0.558***	-0.268**	-0.276**
	(0.058)	(0.058)	(0.056)	(0.056)	(0.110)	(0.110)	(0.090)	(0.092)
30,000 $\leq$ Income <49,999USD	-0.213***	-0.222***	-0.097*	-0.098*	-0.291***	-0.305***	-0.121	-0.121
	(0.042)	(0.042)	(0.039)	(0.039)	(0.074)	(0.075)	(0.062)	(0.064)
50,000 $\leq$ Income <99,999USD	-0.069*	-0.066	-0.005	-0.006	-0.154*	-0.153*	-0.078	-0.081
	(0.034)	(0.034)	(0.029)	(0.029)	(0.060)	(0.060)	(0.049)	(0.051)
Time Since Last Purchase								
First Diaper Purchase	-0.139	-0.141*	-0.074	-0.076	-0.074	-0.073	-0.039	-0.050
	(0.071)	(0.071)	(0.062)	(0.063)	(0.160)	(0.161)	(0.123)	(0.132)
Two weeks or less	-0.175***	-0.168***	-0.110***	-0.112***	-0.057	-0.046	-0.024	-0.030
	(0.039)	(0.038)	(0.033)	(0.033)	(0.073)	(0.074)	(0.054)	(0.055)
Three or four weeks	-0.121**	-0.116**	-0.024	-0.026	-0.060	-0.053	0.012	0.004
	(0.037)	(0.037)	(0.032)	(0.032)	(0.070)	(0.070)	(0.054)	(0.055)
Five or six weeks	-0.019	-0.022	0.018	0.012	-0.056	-0.055	0.017	0.001
	(0.044)	(0.044)	(0.038)	(0.037)	(0.076)	(0.077)	(0.057)	(0.058)
Fixed Effects								
Year	no	yes	yes	yes	no	yes	yes	yes
Retailer	no	no	yes	yes	no	no	yes	yes
Month	no	no	no	yes	no	no	no	yes
Constant	3.853***	3.814***	3.749***	3.691***	-0.305	-0.448	0.689	0.469
	(0.123)	(0.126)	(0.112)	(0.135)	(0.575)	(0.587)	(0.398)	(0.439)
N	2252	2252	2252	2252	2110	2110	2110	2110
adj. R^2	0.164	0.166	0.409	0.408				
First Stage F-test								
Unit Price					79.17	78.51	66.72	60.89
Unit PP Price					165.84	166.44	80.12	78.69

Robust standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Calculations based on data from The Nielsen Company (US), LLC and marketing databases.

Table 2.7: IV Regressions, Informed and Less Informed Consumers

	(1) Uninformed Consumers	(2) Informed Consumer
Prices		
Unit Price Paid	-1.845***	-4.903***
	(0.278)	(1.047)
Unit PP Price	0.711***	0.886*
	(0.156)	(0.408)
Brand		
Pampers	0.949***	2.113***
	(0.140)	(0.488)
Huggies	0.745***	1.887***
	(0.138)	(0.507)
LUVS	0.195	0.467*
	(0.114)	(0.192)
Diaper Size		
Size 1-2	-0.707***	-1.840***
	(0.172)	(0.464)
Size 3	-0.441**	-1.192***
	(0.157)	(0.348)
Size 4	-0.063	-0.723***
	(0.109)	(0.215)
Household Demographics		
Chicago	0.252**	-0.088
	(0.0870)	(0.121)
Size of the Household	-0.094**	-0.046
	(0.031)	(0.034)
White	0.007	0.026
	(0.065)	(0.104)
Income $\leq$ 30,000USD	-0.269	-0.258
	(0.140)	(0.145)
30,000 $\leq$ Income <49,999USD	-0.035	-0.225
	(0.0935)	(0.116)
50,000 $\leq$ Income <99,999USD	0.086	-0.322**
	(0.0873)	(0.118)
Time Since Last Purchase		
First Diaper Purchase	-0.124	
	(0.127)	
Two weeks or less	-0.081	-0.074
	(0.074)	(0.105)
Three or four weeks	0.009	-0.107
	(0.072)	(0.117)
Five or six weeks	0.046	-0.094
	(0.084)	(0.114)
Fixed Effects		
Year	yes	yes
Month	yes	yes
Retailer	yes	yes
Constant	1.702***	-2.647
	(0.433)	(1.446)
N	924	1186
First Stage F-test		
Unit Price	50.22	15.09
Unit PP Price	31.23	26.73

Robust standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Calculations based on data from The Nielsen Company (US), LLC and marketing databases.

price (if on promotion) and whether a consumer is making her first brand purchase. The price paid has the expected negative sign in general. Once interacted with the first purchase indicator, the unit paid price has no significant effect on the quantity purchased.[20] Therefore, the price paid appears not to have any different effect depending on whether consumers are making their first or subsequent purchases. People uninformed about the product may use the price paid as a signal of quality, but this effect cannot be clearly identified apart from the allocative price effect. For its part, the PP price has an overall positive effect. This is compatible with the idea that people like bargains and that it entices them to buy more. However, when it is interacted with the first brand purchase, this effect is negative. This finding is consistent with the idea that when people are uninformed they first try the product in a limited quantity. All regressions include dummies accounting for inter-purchase time to proxy for inventory effects. These variables are not significant except for the first purchase indicator, which is negatively related to the quantity bought.

These presented results shed some light on how quantity decisions are made. The PP price has a positive impact on quantity bought when people are informed about the product's quality but a negative impact when they are making their first purchase. In the next subsection, I look at whether consumers decide to buy at all.

2.5.2 Individual Choice Model

Once an individual is in the store, she decides to buy one of the four leading brands available, to buy another brand, or not to buy diapers at all. The decision is influenced by brand attributes as well as individual characteristics. Each time a household goes to a store, it faces five options: buying Pampers, buying Huggies, buying LUVS, buying the private label brand, or not buying/buying from another brand.[21]

In particular, the individual chooses the brand (conditional on the diaper size) that maximizes her utility. Define the utility of a household i buying brand j at time t as

$$\begin{aligned} U_{ijt} &= V_{ijt} + e_{ijt} \\ &= x_{ijt}\beta + w_{it}\gamma_j + e_{ijt}, \end{aligned}$$

where x_{ijt} are attributes of a particular choice, w_{it} are characteristics of the household and e_{ijt} are the random components. The x_{ijt} thus vary across the choices —and possibly across individuals—while the w_{it} are fixed over choices in t. In my setting I have:

x_{ijt}: price paid, PP price and interactions with the first purchase,

[20] As the first purchase is the result of an exogenous event, I can use the product of the first purchase and the instrument for the price (or PP price) as an instrument for the interaction term (Balli and Sørensen, 2013).

[21] The decisions of not buying at all and buying from another diaper brand are combined into one decision option and labelled as the "outside option."

Table 2.8: IV Regressions, Less Informed Consumers

	(1) IV	(2) IV	(3) IV
Prices			
Unit Price Paid	-1.843***	-1.818***	-1.816***
	(0.280)	(0.276)	(0.274)
Unit PP Price	0.726***	0.800***	0.801***
	(0.159)	(0.179)	(0.178)
Unit Price × First Brand Purchase	-0.105		0.074
	(0.061)		(0.072)
Original Price × First Brand Purchase		-0.445**	-0.501**
		(0.149)	(0.180)
Brand			
Pampers	0.961***	0.952***	0.944***
	(0.141)	(0.139)	(0.137)
Huggies	0.756***	0.743***	0.736***
	(0.140)	(0.137)	(0.135)
LUVS	0.169	0.172	0.187
	(0.113)	(0.105)	(0.106)
Diaper Size			
Size 1-2	-0.729***	-0.703***	-0.687***
	(0.173)	(0.171)	(0.171)
Size 3	-0.448**	-0.446**	-0.442**
	(0.158)	(0.156)	(0.155)
Size 4	-0.065	-0.055	-0.053
Household Characteristics			
Chicago	0.254**	0.253**	0.252**
	(0.088)	(0.087)	(0.087)
Size of the Household	-0.094**	-0.101***	-0.102***
	(0.031)	(0.030)	(0.0303)
White	0.010	-0.0137	-0.0182
	(0.0658)	(0.064)	(0.064)
Income ≤ 30,000USD	-0.277	-0.268	-0.261
	(0.142)	(0.142)	(0.142)
30,000 ≤ Income <49,999USD	-0.033	-0.034	-0.035
	(0.095)	(0.093)	(0.092)
50,000 ≤ Income <99,999USD	0.086	0.096	0.098
	(0.089)	(0.090)	(0.090)
Time Since Last Purchase			
First Diaper Purchase	-0.256	-0.349**	-0.284*
	(0.145)	(0.129)	(0.133)
Two weeks or less	-0.071	-0.067	-0.072
	(0.0751)	(0.0752)	(0.0751)
Three or four weeks	0.024	0.021	0.013
	(0.074)	(0.072)	(0.073)
Five or six weeks	0.059	0.061	0.054
	(0.085)	(0.084)	(0.085)
Fixed Effect			
Year	yes	yes	yes
Month	yes	yes	yes
Retailer	yes	yes	yes
Constant	1.667***	1.767***	1.799***
	(0.437)	(0.430)	(0.426)
N	924	924	924
First Stage F-test			
Unit Price	34.02	35.93	27.02
Unit PP Price	23.40	162.24	159.18
Unit Price × First Purchase	1126.74		812.30
Unit PP Price × First Purchase		609.66	500.75

Robust standard errors in parentheses, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Calculations based on data from The Nielsen Company (US), LLC and marketing databases.

w_{it}: household characteristics.

A household i chooses brand j if this gives it the highest utility. The utility from the outside good (not buying one of the four leading brands) is normalized to

$$U_{i0t} = w_{it}\gamma_0 + e_{i0t}.$$

This means that the individual characteristics enter the utility but the brand characteristics are normalized to zero.

Assuming that the random terms e_{ijt} are iid type I extreme value distributed, the probability that household i chooses brand j in period t is:

$$PR_{ijt} = \frac{\exp(V_{ijt})}{\sum_{k=0}^{J} \exp(V_{ikt})},$$

where J is the total number of brands offered and $j = 0$ corresponds to the outside good.

In order to investigate the price effect of the first purchase, I include an interaction between the price paid, the PP price, and whether it is a first brand purchase. Table 2.9 displays the results of the alternative specific coefficients for different specifications. Table 2.10 reports the individual characteristics for each brand for specification (5) in Table 2.9. The complete tables with individual characteristics for each brand and each specification can be found in Appendix 2.6.

Table 2.9: Alternative Specific Conditional Logit of Purchase Choices

	(1)	(2)	(3)	(4)	(5)
Brand Choice					
Unit Price Paid	-5.402***	-5.426***	-5.730***	-4.686***	-4.557***
	(0.669)	(0.671)	(0.673)	(0.667)	(0.669)
Unit PP Price		-0.111	1.130***	-0.138	-0.353
		(0.254)	(0.273)	(0.256)	(0.281)
Unit PP Price and First Purchase			-4.061***		1.173+
			(0.466)		(0.627)
Unit Price Paid and First Purchase				-5.949***	-6.558***
				(0.390)	(0.520)
N	27190	27190	27190	27190	27190
Log-Likelihood	-3560.083	-3515.518	-3559.987	-3412.016	-3410.277

Standard errors in parentheses, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All specifications include individual characteristics as well as a constant, all interacted with each brand.

Calculations based on data from The Nielsen Company (US), LLC and marketing databases.

As expected, the price paid has a negative effect on the probability of buying a particular brand. The price paid at a first purchase has a similarly significant negative impact on the probability of buying a certain brand. Uninformed consumers may use the price paid as a signal of quality when there is no promotion. However, it is

Table 2.10: Individual Characteristics for Column (5) of Table 2.9

	Pampers	**Huggies**	**LUVS**	**Private Label**
Female under 30	1.186***	1.142***	0.394	1.250***
	(0.246)	(0.294)	(0.613)	(0.279)
Female 30-44	0.374*	0.522***	0.453	1.010***
	(0.147)	(0.158)	(0.313)	(0.183)
Highest Ed: High School	-0.638**	0.727***	-0.398	0.763***
	(0.195)	(0.220)	(0.559)	(0.230)
Highest Ed: College	-0.193	-0.050	0.499	-0.234
	(0.157)	(0.182)	(0.513)	(0.224)
Black	0.225	0.531*	1.309	0.117
	(0.234)	(0.245)	(1.093)	(0.280)
White	0.019	-0.064	1.976^{+}	0.173
	(0.175)	(0.223)	(0.219)	(0.214)
Married	0.318^{+}	-0.121	0.447	0.293
	(0.188)	(0.202)	(0.201)	(0.206)
Chicago	0.117	-0.001	-1.001***	0.869***
	(0.133)	(0.139)	(0.274)	(0.175)
Income 30,000-49,999	0.979**	-0.174	-0.249	-0.112
	(0.350)	(0.284)	(0.477)	(0.257)
Income 50,000-99,000	1.021**	0.089	-0.513	-0.317
	(0.339)	(0.272)	(0.454)	(0.252)
Income 100,000 and over	0.283	0.730*	-2.361***	-0.624*
	(0.361)	(0.294)	(0.754)	(0.294)
Size of the Household	0.020	0.014	0.430***	-0.009
	(0.057)	(0.053)	(0.117)	(0.060)
Constant	-2.125***	-1.907***	-5.416***	-3.137***
	(0.484)	(0.465)	(1.298)	(0.503)

Standard errors in parentheses, $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Calculations based on data from The Nielsen Company (US), LLC and marketing databases.

difficult to distinguish this effect from the usual negative price effect. In general, the PP price—when the brand is on promotion—does not have a clear impact. Focusing on column (5), which is the most complete specification, it can be seen that the PP effect is not significant. However, when it is interacted with the first purchase, it has a positive impact on the choice decision. This is in line with the idea that individuals who are uninformed about a brand use the price they see as a signal of quality. Table 2.10 displays the results on the individual characteristics. The lowest level of educational achievement increases the probability of buying the generic brand. On the other hand, having a very high income decreases the probability of choosing the private label and LUVS.

This subsection shows that the PP price can trigger people's decisions to buy when they are uninformed. While in general, the PP price does not have a significant effect on the probability of purchase, it does have a positive effect when people are uninformed.

2.6 Conclusion

In this paper, I aim to offer insights about how people react to discounted prices. In particular, I investigate the effects of the pre-promotion (PP) price when a product is discounted.

I start by presenting a theoretical learning model that provides an understanding of the mechanisms that may take place. My focus is on experience goods whose characteristics—such as quality—are difficult to know in advance, but can be determined upon consumption (Nelson, 1970). When a product is on sale, people uninformed about its quality may use the PP price as a quality signal. Once people have used the product and they know its quality, the PP price no longer provides information on quality. However, the fact that a price is discounted may directly impact consumers' purchases and utilities. For example, a high PP price can increase an individual's utility because it increases consumers' perceptions of savings (Grewal and Compeau, 2007).

For my empirical analysis, I use panel data from the Nielsen Company on consumer purchases. I consider the disposable diaper category and investigate brand choices. I look at how a PP price impacts the quantity people buy, along with how it impacts their purchase decisions to buy at all. Because of the panel structure of my data, I am able to follow the same consumers over time. I can observe their first purchase—as uninformed consumers—as well as their subsequent purchases. This allows me to distinguish between the signaling effect that the PP price may have and the direct effect that a good deal may have on a consumer's utility.

My findings are consistent with the idea that the PP price is taken into account by people who are uninformed about a brand. This non-discounted price convinces consumers to buy a product even if they are not fully informed about it. However, it does not increase the quantity of the product that they buy. When an individual does not know the quality of a product, she will first try it in a limited quantity. These results may be of interest for marketers who want to enter a new market or attract a new group of consumers. While an uninformed consumer will react positively to the PP price of a product on promotion, she will not increase her purchase quantity. In this sense, it may not be optimal to make such a product available in a large quantity for this type of consumer.

Further research is needed to investigate these mechanisms with other products. Diapers are a useful category because uniformed consumers are easily observable. However, it would be interesting to investigate a totally new product through a similar research method. In my empirical findings, once a consumer has tried the product, she knows the quality and I assume that the quality signal does not come into play. It could be, however, that a consumer needs more than one trial to perfectly know the product's quality. If this is the case, my findings on the signaling effect of the PP price can be considered as a lower bound of the total signaling effect.

Despite its limitations, this work provides interesting insights about how and why people react to discounted prices. The literature on discount pricing itself has received little economic analysis (Armstrong and Chen, 2013) and this work makes a contribution to the field.

Acknowledgment

I thank my supervisor, Michelle Sovinsky, for her support and comments. I further thank Uli Kaiser, Greg Crawford, Andràs Péchy, seminar participants at the University of Zurich and at the BI Norwegian Business School in Oslo. Tables and figures presented in this paper are based on data from The Nielsen Company (US), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. Information on availability and access to the data is available at http://research.chicagobooth.edu/nielsen.

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Appendix

Details of the Learning Model

In Section 2.3, the general features of a learning model are presented. More details are discussed in this section.

Consumer i does her shopping in period t and faces products $j = 1, ..., J$. The price paid is denoted p_{ijt}. The discount (if any) is denoted by d_{it} and the price without discount—the pre-promotion (PP) price—is denoted by P_{ijt}. Thus $P_{ijt} = p_{ijt} - d_{ijt}$. If there is no discount, the price paid is equal to the PP price. The PP price serves as a signal for consumers[22] and they use it when making inferences about product quality.[23] The good considered is an experience good and is assumed to be nondurable enough that it is consumed before the next purchase (as in Ackerberg, 2003). In a given period, consumers observe prices of all the products available—as well as their discounts—and decide to purchase one of the products or the outside alternative.

Following Erdem et al. (2008), I assume the following form for the utility function:

$$U_{ijt} = \alpha_i p_{ijt} + \beta_i Q^E_{ijt} + \beta_i r_i \left(Q^E_{ijt}\right)^2 + \gamma_i D_{ijt} + e_{ijt},$$

where p_{ijt} is the price paid by the consumer for this product, Q^E_{ijt} is the "experience quality" (Erdem et al., 2008) or "experience utility" (Ackerberg, 2003), r_i represents the consumer's risk aversion towards variations in quality, D_{ijt} is the deviation from the reference price (details below) and e_{ijt} is a taste shock known to the consumer but not to the econometrician.

Experience quality, Q^E_{ijt} is the measure of the utility that consumer i derives from product characteristics that are not directly observable to her and are not known before the purchase. The Q^E_{ijt} might, for example, how long it takes to experience the first leak in the diaper. Once the good is purchased and used, Q^E_{ijt} is revealed. The simplest case is a one-period learning process where Q^E_{ijt} is constant for all future periods. In that case, after one purchase, the consumer knows the experience utility

[22] This is unlike Erdem et al., 2008 who assume that the price signal always comes from the price paid.

[23] When a product is presented at "50USD instead of 100USD", I assume that people use 100USD to infer quality rather than 50USD.

for all future t. The general way of writing the learning process is:

$$Q_{ijt}^E = Q_j + \xi_{ijt} \text{ where } \xi_{ijt} \sim \ N(0, \sigma_\xi^2). \tag{2.5}$$

Q_j is the true quality of the product, but consumers do not experience it directly as the user's experience is context dependent (Erdem et al., 2008). The ξ_{ijt} correspond to the experience variability and are not distinguishable from the mean. When $\sigma_\xi^2 = 0$, corresponds to the one period learning, where $Q_{jt}^E = Q_j$.

Before any experience in the market, at $t = 0$, individuals have some priors about the mean prices and the mean experience quality level of products. Consumers perceive that the true quality of product j is distributed normally with mean Q_{j0} and variance σ_{j0}^2:

$$Q_j \sim N(Q_{j0}, \sigma_{j0}^2).$$

The use experience gives households signals about the product's quality (Erdem and Keane, 1996). Let $Q_{ijt}^S \equiv E(Q_j|S_{it})$ be the household's perceived quality for product conditional on information (i.e., signals) at time t (the information set S_{it}), $N_{ij}\,(t)$ is the total number of use experience signals household i has received up to t and b_{ijt} equals 1 if product j is bought in time t. The updated perceived quality can then be written as (Erdem and Keane, 1996):

$$Q_{ijt}^S = \frac{\sigma_{j0}^2}{N_{ij}(t)\sigma_{j0}^2} \Sigma_{s=1}^{t-1} Q_{ijs}^E b_{ijs},$$

and the perceived variance is

$$\sigma_{ijt}^2 = \frac{1}{(1/\sigma_{j0}^2) + N_{ij}(t)(1/\sigma_\xi^2)}$$

(see DeGroot, 1970).

In addition, people may use the PP price as a signal of quality. It is assumed that the PP prices observed by the consumers, P_{ijt}, follow the process

$$P_{ijt} = P_j + \omega_{ijt}, \quad \omega_{ijt} \sim N(0, \sigma_\omega^2), \tag{2.6}$$

where P_j is the mean PP price. Deviations around the mean P_j exist because some consumers may not see the PP price posted during a promotion, or there may be some variations in where and when the PP price is posted. Consumers believe that this mean price is related to the product quality as follows (Erdem et al., 2008):

$$P_j = \phi_0 + \phi_1 Q_j + \eta_j, \tag{2.7}$$

where Q_j is the product's true quality as presented above. The η_j account for the fact that a certain product may deviate from the typical price/quality relationship, and have a price that is too high or too low. Consumers perceive that the η_j are distributed according to $\eta_j \sim N(0, \sigma_\eta^2)$.

Consumers use the observed P_{ijt} to learn about P_j. Thus, combining (2.6) and (2.7) gives

$$P_{ijt} = \phi_0 + \phi_1 Q_j + \eta_j + \omega_{ijt},$$

where ϕ_0, ϕ_1 and σ_ω^2 would have to be estimated[24] Note that while the price observed by the consumer P_{ijt} is indexed by i (various consumers see different prices), the true quality Q_j is product specific.

The prior for the mean price can be written as[25]

$$P_j \sim N(\phi_0 + \phi_1 Q_{j0}, \phi_1^2 \sigma_{j0}^2 + \sigma_\eta^2) \text{ for } j = 1, ..., J.$$

The consumer's prior is that the true mean price has a variance equal to $\phi_1^2 \sigma_{j0}^2 + \sigma_\eta^2$. Thus, a product can have an above average price because it is of high quality— $\phi_1^2 \sigma_{j0}^2$ —or because it is priced too high given its quality—σ_η^2 (Erdem et al. 2008).

The PP price also gives some signals of quality to the consumer and, therefore, the perceived quality, including the price signal, are updated. As before, the household's perceived quality is $Q_{ijt}^S \equiv E(Q_j | S_{it})$. I further let $P_{ijt}^S \equiv E(P_j | S_{it})$ be the household's perceived PP price for product j conditional on information (i.e., signals) at time t (the information set S_{it}). At $t = 0$, these are $Q_{ij0}^S = Q_{ij0} = Q_{j0}$ and $P_{ij0}^S = \phi_0 + \phi_1 Q_{j0}$. As mentioned, $N_{ij}(t)$ is the the total number of use experience signals household i received up to t. $M_{ij}(t)$ is defined as the total number of PP price signals household i received up to t. These two numbers must not be the same. People do not necessarily get experience quality signals every period as they only get a signal if they buy and use the product. However, people are assumed to face price signals every time they buy one product of the considered category. If person i buys product $g \neq j$ (from the same category), she is assumed to get a price signal from product g and from product j as well.

Both signals—use experience and PP price—impact the consumer's perceived quality. The whole process can be written (Ackerberg, 2003; DeGroot, 1970) as a

[24] Both ϕ_0 and a value of η_j cannot be estimated for each brand. Thus, the η_j are assumed to be mean zero across brands, $\sum_{j=1}^{J-1} \eta_j = \eta_J$ (Erdem et al., 2008).

[25]

$$\begin{aligned} E(P_j) &= E(\phi_0 + \phi_1 Q_j + \eta_j) \\ &= E(\phi_0) + \phi_1 E(Q_j) + E(\eta_j) \\ &= \phi_0 + \phi_1 Q_{j0} \end{aligned}$$

$$\begin{aligned} Var(P_j) &= E((P_j)^2) - (E(P_j))^2 \\ &= E\left((\phi_0 + \phi_1 Q_j + \eta_j)^2\right) - \left[E\left(\phi_0 + \phi_1 Q_j + \eta_j\right)\right]^2 \\ &= \phi_1^2 \sigma_{j0}^2 + \sigma_\eta^2 \end{aligned}$$

combination of initial priors at $t = 0$:

$$\begin{pmatrix} Q_j \\ P_j \end{pmatrix} \sim N\left(\begin{pmatrix} Q_{j0} \\ \phi_0 + \phi_1 Q_{j0} \end{pmatrix}, \begin{bmatrix} \sigma_{j0}^2 & \phi_1 \sigma_{j0}^2 \\ \phi_1 \sigma_{j0}^2 & \phi_1^2 \sigma_{j0}^2 \end{bmatrix} \right),$$

learning process:

$$\begin{pmatrix} Q_{ijt}^E \\ P_{ijt} \end{pmatrix} \sim N\left(\begin{pmatrix} Q_j \\ P_j \end{pmatrix}, \begin{bmatrix} \sigma_\xi^2 & 0 \\ 0 & \sigma_\omega^2 \end{bmatrix} \right),$$

and consumer's updated beliefs about the product j after a history of observed PP prices and use experiences:

$$\begin{pmatrix} Q_j \\ P_j \end{pmatrix} \sim N\left(s_{it}, \Sigma_{it}\right),$$

where

$$s_{it} = \begin{pmatrix} Q_{ijt}^S \\ P_{ijt}^S \end{pmatrix} =$$

$$\left(\begin{bmatrix} \sigma_{j0}^2 & \phi_1 \sigma_{j0}^2 \\ \phi_1 \sigma_{j0}^2 & \phi_1^2 \sigma_{j0}^2 + \sigma_\eta^2 \end{bmatrix}^{-1} + \begin{bmatrix} N_{ij}(t) & 0 \\ 0 & M_{ij}(t) \end{bmatrix} \begin{bmatrix} \sigma_\xi^2 & 0 \\ 0 & \sigma_\omega^2 \end{bmatrix}^{-1} \right)^{-1}$$
$$\left(\begin{bmatrix} \sigma_{j0}^2 & \phi_1 \sigma_{j0}^2 \\ \phi_1 \sigma_{j0}^2 & \phi_1^2 \sigma_{j0}^2 + \sigma_\eta^2 \end{bmatrix}^{-1} \begin{pmatrix} Q_{j0} \\ \phi_0 + \phi_1 Q_{j0} \end{pmatrix} + \begin{bmatrix} N_{ij}(t) & 0 \\ 0 & M_{ij}(t) \end{bmatrix} \begin{bmatrix} \sigma_\xi^2 & 0 \\ 0 & \sigma_\omega^2 \end{bmatrix}^{-1} \begin{pmatrix} \frac{1}{N_{ij}(t)} \sum_{k=1}^{N_{ij}(t)} Q_{ijk}^E \\ \frac{1}{M_{ij}(t)} \sum_{\tau=1}^{M_{ij}(t)} P_{ijt} \end{pmatrix} \right)$$

and

$$\Sigma_{it} = \left(\begin{bmatrix} \sigma_{j0}^2 & \phi_1 \sigma_{j0}^2 \\ \phi_1 \sigma_{j0}^2 & \phi_1^2 \sigma_{j0}^2 + \sigma_\eta^2 \end{bmatrix}^{-1} + \begin{bmatrix} N_{ij}(t) & 0 \\ 0 & M_{ij}(t) \end{bmatrix} \begin{bmatrix} \sigma_\xi^2 & 0 \\ 0 & \sigma_\omega^2 \end{bmatrix}^{-1} \right)^{-1}$$

The discount is assumed to enter the utility function directly via $\gamma_i D_{ijt}$. In particular,

$$\gamma_i D_{ijt} = \gamma_1 I_{ijt}(RP_{ijt} - p_{ijt}) + \gamma_2(1 - I_{ijt})(p_{ijt} - RP_{ijt}). \tag{2.8}$$

RP_{ijt} corresponds to the reference price of person i in time t for product j, $I_{ijt} = \begin{cases} 1 \text{ if } RP_{ijt} > p_{ijt} \\ 0 \text{ if } RP_{ijt} < p_{ijt} \end{cases}$ is a dummy variable indicating whether the individual is incurring a gain or a loss compared to her reference price. This allows me to incorporate loss aversion as well as bargain loving. The coefficients are allowed to differ as losses may hurt more than gains (if people are more loss averse than bargain loving) or inversely (Armstrong and Chen, 2013). Thus $D_{ijt} = \begin{cases} (RP_{ijt} - p_{ijt}) \text{ if } RP_{ijt} > p_{ijt} \\ (p_{ijt} - RP_{ijt}) \text{ if } RP_{ijt} < p_{ijt} \end{cases}$. D_{ijt} can be equal to the current discount (d_{ijt}) if the reference price is the past price, but they may differ. Consumers may develop an anchor (or not) and use it to compare with the presented price. The reference price impacts the way consumers perceive products and may impact their choices. More details on how I define the reference price are provided below in the reference price subsection.

The expected utility of household i from using product j in time t can be written as:

$$E[U_{ijt}|S_{it}] = \alpha_i p_{ijt} + \beta_i E\left[Q^E_{ijt}|S_{it}\right] + \beta_i r_i E\left[\left(Q^E_{ijt}\right)^2|S_{it}\right] + \gamma_i D_{ijt} + e_{ijt},$$

where S_{it} refers to the information set of a household that contains all signals consumer i has received until t. I assume that the signals are unbiased and thus $E\left[Q^E_{ijt}|S_{it}\right] = E\left[Q_j|S_{it}\right] = Q^S_{ijt}$. Writing $Q^E_{jt} = Q^S_{ijt} + (Q_j - Q^S_{ijt}) + \xi_{ijt}$ results in:

$$E[U_{ijt}|S_{it}] = \alpha_i p_{ijt} + \beta_i Q^S_{ijt} + \beta_i r_i \left(Q^S_{ijt}\right)^2 + \beta_i r_i E\left[\left(Q_j - Q^S_{ijt}\right)^2|S_{it}\right] + \gamma_i D_{ijt} + \beta_i r_i \sigma^2_\xi + e_{ijt}.$$

With this formulation, it can be seen that there are two sources of expected variability of consumer's experienced quality: First, the experienced variability σ^2_ξ; and second, the variability of the experienced quality around the true quality $\left[\left(Q_j - Q^S_{ijt}\right)^2|S_{it}\right]$ (Erdem et al., 2008). The no purchase option is defined as

$$E[U_{i0t}|S_{it}] = \Theta + e_{i0t}$$

Both the PP price and usage give information to the consumer on true brand quality Q_j. However, while buying and using the product gives direct information on Q_j, the PP price only provides indirect information through the consumer's prior beliefs that PP price and quality are correlated. The more direct information the consumer acquires via using the product, the less she needs indirect information through the PP price. Therefore, all else equal, the more usage experience an individual has, the less information will come from the PP price signal and the less it will impact her expected utility function. In a one-usage learning model (where true quality is learned after one use only), the PP price will have no impact on a consumer after she has bought the product once (Ackerberg, 2003).

Reference Price

People may develop an anchor (consciously or not) and compare it to the presented price. The reference price (RP) impacts the way consumers perceive products and may impact their choices. There are several ways the RP actually enters the utility function. As stated in the literature review, there are predominantly two types of RP: the internal reference price (IRP) and the external reference price (ERP) (Mayhew and Winer, 1992). What is not entirely clear form the literature is whether people have one RP for each product/brand or a general one for the category. Reference price impacts can also be considered as an approximation for inventory. For example, people will buy only if the price is lower than their RP and, in that case, they may buy more than usual (to form a stockpile). In my model, I allow for different specifications of the RP.

External Reference Price: Pre-Promotion Price

An external reference price refers to an external stimulus perceived by an individual that may impact her product choice. In my setting, it represents the PP price that is displayed along with the price paid. As stated above, the PP price is also the price consumers use to make inferences about some quality of the product about which they are unsure. Thus, in this specification, the PP price has a double role when people are still learning about the quality of the product. Once its quality is known, only the role as RP is present. I take inspiration from the way Ackerberg (2003) models the prestige or image impact of advertising. In particular, uninformed people learn something about the product's quality by observing the PP price. But, at the same time, people have a perceived PP price measure for each product which is denoted P^S_{ijt} (the element that is updated in the learning process above). As in Ackerberg (2003), once people know about the product's quality, only this direct effect remains while the signaling effect vanishes. Thus, in this case, equation (2.8) can be written as follows:

$$\gamma_i D_{ijt} = \gamma_1 I_{ijt}(P^S_{ijt} - p_{ijt}) + \gamma_2(1 - I_{ijt})(p_{ijt} - P^S_{ijt}). \tag{2.9}$$

As noted above, people update their perceived PP price for a particular brand every time they purchase a product in this category. This is also in line with the price consideration model of Ching et al. (2009).

It is possible that the price paid is always the PP price; that is, there is no discount at all and $P^S_{ijt} = p_{ijt}$. In these cases, there is only the usual price effect and this channel shuts down automatically. By construction, consumers will mostly experience a gain in this definition of RP. Indeed, the PP price is by definition equal to or higher than the price paid except if a manufacturer suddenly raises its prices.

Internal Reference Price: Price Paid

There are some papers (for example, Erdem et al., 2010) claiming that frequent discounts may lower consumers' RP. The underlying idea is that people use the price paid as an RP—rather than the PP price—and, therefore, discounts reduce their reference point. For this specification, I take inspiration from Mayhew and Winer (1992) and use the previous price of the considered product in the same store (p_{t-1}) as a proxy for the consumer's IRP. As noted by Erdem et al. (2010), "[u]pdating reference prices only when households make purchases would underestimate the reference price" ; thus, again, I allow people to update their RP for a particular product j even if they do not buy this very product. Contrary to the RP from the first specification, here I am interested in the price paid in the last period (or the price that would have been paid in the last period). Equation (2.8) becomes

$$\gamma_i D_{ijt} = \gamma_1 I_{ijt}(p^C_{ijt-1} - p_{ijt}) + \gamma_2(1 - I_{ijt})(p_{ijt} - p^C_{ijt-1}), \tag{2.10}$$

where p^C_{ijt-1} is the previous actual price of product j during the last period the consumer considered the category.[26] If a product was on sale during the last period and is not on sale this period, consumers may get less utility and I expect γ_2 to be negative. Here again, if the price of a product does not change, then $p_{ijt} = p^C_{ijt}$ and this effect disappears.

I do not follow the same concept as Erdem et al. (2008) who state that people use the price paid also to infer quality. Instead, I maintain my idea that consumers use the PP price to infer quality (Monroe and Chapman,1987).

Conditional Logit Complete Tables

Table 2.11: Alternative Specific Conditional Logit for Purchase Choices

	(1) choice	(2) choice	(3) choice	(4) choice	(5) choice
Brand Choice					
Unit Price Paid	-5.402***	-5.426***	-5.730***	-4.686***	-4.557***
	(0.669)	(0.671)	(0.673)	(0.667)	(0.669)
Unit PP Price		-0.111	1.130***	-0.138	-0.353
		(0.254)	(0.273)	(0.256)	(0.281)
Unit PP Price and First Purchase			-4.061***		1.173+
			(0.466)		(0.627)
Unit Price Paid and First Purchase				-5.949***	-6.558***
				(0.390)	(0.520)
N	27190	27190	27190	27190	27190

Standard errors in parentheses, $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
All specifications include individual characteristics as well as a constant, all interacted with each brand.
Calculations based on data from The Nielsen Company (US), LLC and marketing databases.

[26] It is indexed by $t-1$, but the price considered may come from $t-1$, $t-2$, ... depending on the last time consumer bought this product.

Table 2.12: Individual Characteristics for Pampers

	(1)	(2)	(3)	(4)	(5)
Female under 30	1.181***	1.182***	1.175***	1.187***	1.186***
	(0.242)	(0.242)	(0.243)	(0.246)	(0.246)
Female 30-44	0.063	0.064	0.176	0.376*	0.374*
	(0.140)	(0.140)	(0.142)	(0.147)	(0.147)
Highest Ed: High School	-0.759***	-0.758***	-0.704***	-0.638**	-0.638**
	(0.193)	(0.193)	(0.193)	(0.195)	(0.195)
Highest Ed: College	0.000	0.001	-0.077	-0.194	-0.193
	(0.152)	(0.152)	(0.154)	(0.157)	(0.157)
Black	-0.008	-0.007	0.082	0.229	0.225
	(0.220)	(0.220)	(0.224)	(0.234)	(0.234)
White	-0.199	-0.196	-0.118	0.0213	0.0186
	(0.163)	(0.163)	(0.166)	(0.175)	(0.175)
Married	0.297	0.297	0.316+	0.321+	0.318+
	(0.185)	(0.185)	(0.186)	(0.188)	(0.188)
Chicago	0.193	0.194	0.151	0.115	0.117
	(0.129)	(0.129)	(0.130)	(0.133)	(0.133)
Income 30,000-49,999	1.078**	1.077**	1.061**	0.982**	0.979**
	(0.343)	(0.343)	(0.345)	(0.350)	(0.350)
Income 50,000-99,000	1.370***	1.371***	1.246***	1.020**	1.021**
	(0.334)	(0.334)	(0.336)	(0.339)	(0.339)
Income 100,000 and over	0.429	0.430	0.398	0.287	0.283
	(0.357)	(0.356)	(0.358)	(0.361)	(0.361)
Size of the Household	0.005	0.006	0.014	0.020	0.020
	(0.0524)	(0.0524)	(0.0540)	(0.0568)	(0.0568)
Constant	-2.301***	-2.288***	-2.247***	-2.120***	-2.125***
	(0.475)	(0.476)	(0.478)	(0.484)	(0.484)

Standard errors in parentheses, $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Calculations based on data from The Nielsen Company (US), LLC and marketing databases.

Table 2.13: Individual Characteristics for Huggies

	(1)	(2)	(3)	(4)	(5)
Female under 30	1.024***	1.029***	1.041***	1.138***	1.142***
	(0.278)	(0.278)	(0.282)	(0.294)	(0.294)
Female 30-44	0.550***	0.551***	0.542***	0.522***	0.522***
	(0.152)	(0.152)	(0.153)	(0.158)	(0.158)
Highest Ed: High School	0.478*	0.481*	0.538*	0.725***	0.727***
	(0.209)	(0.210)	(0.212)	(0.220)	(0.220)
Highest Ed: College	-0.0474	-0.0464	-0.0599	-0.0497	-0.0503
	(0.177)	(0.177)	(0.178)	(0.182)	(0.182)
Black	0.795**	0.797***	0.730**	0.536*	0.531*
	(0.242)	(0.242)	(0.242)	(0.245)	(0.245)
White	-0.058	-0.057	-0.03	-0.059	-0.064
	(0.214)	(0.214)	(0.216)	(0.219)	(0.219)
Married	-0.017	-0.015	-0.045	-0.115	-0.121
	(0.189)	(0.189)	(0.192)	(0.201)	(0.201)
Chicago	-0.204	-0.204	-0.127	-0.000	-0.001
	(0.137)	(0.137)	(0.138)	(0.139)	(0.139)
Income 30,000-49,999	-0.208	-0.207	-0.187	-0.174	-0.174
	(0.271)	(0.271)	(0.275)	(0.284)	(0.284)
Income 50,000-99,000	0.004	0.005	0.030	0.087	0.089
	(0.260)	(0.261)	(0.264)	(0.272)	(0.272)
Income 100,000 and over	0.523+	0.522+	0.592*	0.730*	0.730*
	(0.283)	(0.283)	(0.286)	(0.294)	(0.294)
Size of the Household	0.011	0.011	0.005	0.013	0.014
	(0.0540)	(0.0541)	(0.0535)	(0.0534)	(0.0534)
Constant	-1.956***	-1.942***	-1.928***	-1.903***	-1.907***
	(0.454)	(0.455)	(0.456)	(0.465)	(0.465)

Standard errors in parentheses, $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Calculations based on data from The Nielsen Company (US), LLC and marketing databases.

Table 2.14: Individual Characteristics for LUVS

	(1)	(2)	(3)	(4)	(5)
Female under 30	-0.202	-0.200	-0.064	0.384	0.394
	(0.606)	(0.606)	(0.602)	(0.611)	(0.613)
Female 30-44	0.286	0.287	0.319	0.449	0.453
	(0.306)	(0.306)	(0.307)	(0.313)	(0.313)
Highest Ed: High School	-0.435	-0.434	-0.423	-0.395	-0.398
	(0.548)	(0.548)	(0.550)	(0.559)	(0.559)
Highest Ed: College	0.537	0.536	0.536	0.503	0.499
	(0.506)	(0.506)	(0.506)	(0.513)	(0.513)
Black	1.493	1.493	1.469	1.317	1.309
	(1.081)	(1.081)	(1.083)	(1.093)	(1.093)
White	2.202*	2.204*	2.184*	1.988+	1.976+
	(1.028)	(1.028)	(1.028)	(1.031)	(1.031)
Married	0.542	0.543	0.545	0.454	0.447
	(0.426)	(0.426)	(0.426)	(0.426)	(0.426)
Chicago	-1.073***	-1.072***	-1.045***	-1.001***	-1.006***
	(0.270)	(0.270)	(0.270)	(0.274)	(0.274)
Income 30,000-49,999	-0.631	-0.631	-0.539	-0.256	-0.249
	(0.467)	(0.467)	(0.467)	(0.476)	(0.477)
Income 50,000-99,000	-0.939*	-0.938*	-0.811+	-0.511	-0.513
	(0.430)	(0.430)	(0.432)	(0.453)	(0.454)
Income 100,000 and over	-3.115***	-3.116***	-2.968***	-2.381**	-2.361**
	(0.739)	(0.739)	(0.740)	(0.753)	(0.754)
Size of the Household	0.532***	0.532***	0.513***	0.433***	0.430***
	(0.117)	(0.117)	(0.117)	(0.117)	(0.117)
Constant	-6.131***	-6.123***	-6.038***	-5.447***	-5.416***
	(1.259)	(1.259)	(1.265)	(1.296)	(1.298)

Standard errors in parentheses, + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Calculations based on data from The Nielsen Company (US), LLC and marketing databases.

Table 2.15: Individual Characteristics for Private Label

	(1)	(2)	(3)	(4)	(5)
Female under 30	1.276***	1.280***	1.269***	1.254***	1.250***
	(0.276)	(0.276)	(0.277)	(0.279)	(0.279)
Female 30-44	0.948***	0.948***	0.973***	1.012***	1.010***
	(0.182)	(0.182)	(0.182)	(0.183)	(0.183)
Highest Ed: High School	0.994***	0.996***	0.922***	0.764***	0.763***
	(0.234)	(0.234)	(0.233)	(0.230)	(0.230)
Highest Ed: College	-0.118	-0.117	-0.148	-0.231	-0.234
	(0.227)	(0.227)	(0.226)	(0.224)	(0.224)
Black	0.191	0.193	0.166	0.122	0.117
	(0.283)	(0.283)	(0.282)	(0.280)	(0.280)
White	0.307	0.306	0.260	0.174	0.173
	(0.218)	(0.218)	(0.217)	(0.214)	(0.214)
Married	0.440*	0.441*	0.405*	0.297	0.293
	(0.206)	(0.206)	(0.205)	(0.206)	(0.206)
Chicago	0.830***	0.833***	0.857***	0.875***	0.869***
	(0.168)	(0.168)	(0.170)	(0.175)	(0.175)
Income 30,000-49,999	-0.222	-0.219	-0.149	-0.101	-0.112
	(0.254)	(0.254)	(0.255)	(0.257)	(0.257)
Income 50,000-99,000	-0.455+	-0.451+	-0.382	-0.308	-0.317
	(0.253)	(0.253)	(0.252)	(0.252)	(0.252)
Income 100,000 and over	-0.559+	-0.557+	-0.562*	-0.618*	-0.624*
	(0.289)	(0.289)	(0.287)	(0.282)	(0.282)
Size of the Household	-0.034	-0.033	-0.019	-0.007	-0.009
	(0.060)	(0.060)	(0.060)	(0.060)	(0.060)
Constant	-3.655***	-3.651***	-3.544***	-3.156***	-3.137***
	(0.499)	(0.499)	(0.499)	(0.504)	(0.503)

Standard errors in parentheses, $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Calculations based on data from The Nielsen Company (US), LLC and marketing databases.

Chapter 3

Risky Lifestyle Behaviors and Breast Cancer Diagnosis

joint project with Michelle Sovinsky [1] and Steven Stern [2]

3.1 Introduction

The National Cancer Institute spent more than $550 million in 2013 to investigate the causes of breast cancer (NCI Annual Factbook).[3] According to the Surveillance Epidemiology and End Results Program, almost 13% of US women will develop breast cancer at some point during their life.[4] Furthermore, the incidence of breast cancer is rising worldwide, and its impact is high in terms of mortality, costs of treatment, and emotional impact on the individual and family (Parkin et al., 2005).[5] There are many avenues of research that require funding regarding the breast cancer, including treatment and research into the biological causes.

Perhaps surprisingly, a large proportion of the donations for breast cancer research are spent on public education (43%).[6] An important question concerns therefore whether and how women react to information. However, little research has been undertaken to precisely examine how women react to information about the state of their health. Learning more about the trade-offs a woman makes between unhealthy (but enjoyable) habits and increasing her life expectancy is the focus of this paper.

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[3] http://www.cancer.gov/about-nci/budget/fact-book/data/research-funding

[4] http://seer.cancer.gov/statfacts/html/breast.html

[5] For the United States, Campbell and Ramsey (2009) report an estimate of lifetime per-patient cost of breast cancer going from $20,000 to $100,000. Similarly, Mariotto et al. (2011) report that annual costs of care for breast cancer for women younger than 65 is $27,693 in the initial phase of care and $94,284 during the last year of life.

[6] http://www.reuters.com/article/us-usa-healthcare-komen-research-idUSTRE8171KW20120208

The medical literature reports that several lifestyle habits are associated with breast cancer risk including weight gain, fat intake, and level of physical activity (Demark-Wahnefried et al., 2000; McTiernan et al., 2003; Holmes, 2004; Bellizzi et al., 2005). Weight gain and being overweight are commonly recognized risk factors for breast cancer, with overweight women most commonly observed to be at increased risk of post-menopausal breast cancer and at reduced risk of pre-menopausal breast cancer (Morimoto et al., 2002; Feigelson et al., 2006; Eliassen et al., 2006). Sedentary lifestyle is also a risk factor (Blanchard et al., 2004). Other risk factors include those that are only weakly associated with breast cancer and those that have been inconsistently associated with the disease in epidemiologic studies (Hamajima et al., 2002; Bellizzi et al., 2005). These include alcohol consumption (Singletary and Gapstur, 2001; Hamajima et al., 2002; Aronson, 2003; Coups and Ostroff, 2005; Terry et al., 2006) and cigarette smoking (Demark-Wahnefried et al., 2000; Pinto et al., 2002; Hewitt et al., 2003; Blanchard et al., 2004).

Using rich data from the Panel Study of Income Dynamics on breast cancer diagnosis and lifestyle choices, we estimate how being diagnosed influences smoking, drinking, and exercising habits for more than 9,000 women over the period 1999 to 2011. We find that women who are recently diagnosed with breast cancer decrease the amount of cigarettes they smoke, but they do not change their drinking habits. In addition, women who are diagnosed with breast cancer exercise less, which is perhaps not surprising given that women often undergo treatment after a breast cancer diagnosis that can weaken them and make it more difficult to engage in extra physical activity. Our results suggest that women react to information about their health; particularly those who have been newly diagnosed.

Several studies exist on the role of health behaviors of cancer survivors (in addition to those cited above, see Bellizi et al. (2005) and the references therein). Each of these studies suffers from at least one of the following: it does not use a nationally representative sample or does not address selection bias, does not (or cannot) address changes in behaviors over time, does not correct for endogeneity of health behaviors and cancer outcomes, or does not include relevant control variables (demographics, age, physical limitations) in examining health behaviors and cancer outcomes. Our study addresses these issues.

The paper proceeds as follows. In the next section, we provide an overview of the data. In section 3.3, we present a framework that links breast cancer diagnosis and risky lifestyle choices. We discuss the estimation methodology in section 3.4. We present the results and conclusions in sections 3.5 and 3.6, respectively.

3.2 Data

Our research uses data from the Panel Study of Income Dynamics (PSID). The PSID is a longitudinal study that started in 1968 with over 18,000 individuals from 5,000 households in the United States and now includes more than 22,000 individuals from over 9,000 households. One person per family, designated as the “head,” is interviewed regularly and answers questions about himself, his spouse (or his long-term female cohabitator) and his family members.[7] Families from the core sample are interviewed biennially.[8] Every wave contains information about employment, income, education, wealth, marriage, childbearing, and various other topics. We choose to use the PSID data set because of its longitudinal structure which allows us to follow the same individuals and their corresponding behaviors across time. Further, these data are collected not only for breast cancer patients but also for persons without a history of cancer. This allows us to make comparisons between breast cancer patients and healthy individuals.

We use data from 7 waves from 1999, when cancer outcomes were first recorded, until 2011. We keep female respondents, aged 15 and older, because breast cancer almost exclusively affects women. Our starting sample consists of $9,447$ women for a total of $46,061$ persons-years. Table 3.1 provides an overview of our missing values analysis. First, we drop individuals who have missing values for questions related to demographics,[9] cancer condition and breast cancer condition. We lose a total of 310 persons and are left with a sample of $9,137$ persons and $42,875$ persons-years. Secondly, we use this sample as a new starting point and drop missing values depending on our interest. For our analysis on "smoking behaviors", we only drop observations missing for questions related to smoking habits. Similarly, when looking at "exercise behaviors", we only drop missing values related to exercise habits. This is shown in the bottom panel of Table 3.1.[10]

Table 3.1: Missing Values Analysis

Variables of Interest	Starting # Person-Years	Starting # Persons	# Person-Years Dropped	#Persons Dropped
Explanatory Variables	46061	9447		
Demographics[1]			2999	238
Cancer Condition			37	6
Breast Cancer Condition			150	66
Dependent Variables	42875	9137		
Smoking Habits			39	1
Drinking Habits			55	0
Exercising Habits			251	10

[1] Demographics corresponds to age, race, education level, and income.

Table 3.2 reports demographic summary statistics and Table 3.3 health behaviors

[7] The head can be a man or a woman. Because it is more often the husband, we use the masculine form to refer to it.

[8] As mentioned, the head of the household is often the husband, who will provide answers to for questions related to his spouse. The literature has however shown that spouses have very careful perceptions of the time spent by the other spouse on different activities (Stern, 2003). Similarly, it has been shown (see for example Kolonel et al., 1977; Campbell et al., 2007) that spouses provide complete information for various lifestyle behaviors of their spouse such as smoking and drinking behaviors.

[9] This corresponds to missing values for age, race, education level, or income.

[10] For example, our analysis of "exercising behaviors" is based on a sample of $9,137 - 10 = 9,127$ persons and $42,875 - 251 = 42,624$ persons-years.

summary statistics of our sample. The PSID was initially designed to study the

Table 3.2: Demographics Summary Statistics

Variable	**Mean**	**Std. Dev.**
Age	44.577	15.993
White	0.579	0.494
Black	0.307	0.461
Married	0.638	0.481
Employed	0.637	0.481
Has Children	0.810	0.392
Highest Education Degree:		
No Degree	0.172	0.377
High School	0.415	0.493
University	0.325	0.469
Post Graduate	0.087	0.282
Taxable Income:		
$<$ \$ 20,000	0.196	0.397
\$ 20,000 - \$ 50,000	0.247	0.431
$>$ \$ 50,000	0.557	0.497
Diagnosed with:		
Cancer	0.084	0.277
Breast Cancer	0.021	0.143
Number of Persons-Years:	42875	

dynamics of income and poverty. The oversampling of families who were poor in the late 1960s resulted in a substantial subsample of African Americans (PSID, 2013). In our sample, we also have a large proportion of African American respondents (30%).

One of our main interests is the health status of our respondents and, in particular, their cancer status. As can be seen in Table 3.2, 8.1% of the sample have been diagnosed with cancer and 2% with breast cancer. In our sample, 25% of all cancers diagnosed are breast cancer which matches national breast cancer statistics (American Cancer Society, 2007). As can be seen in Table 3.3, approximately 53% of our respondents ever drink alcoholic beverages, which is slightly below the national average of 55%[11] as reported by the National Center for Health Statistics (Schoenborn and Adams, 2010) for the period 2005-2007.[12] As the survey questions concerning alcohol consumption were not consistently worded across waves,[13] we report statistics

[11] They report the proportion of current drinkers, which refer to adults who have had at least 12 drinks in their lifetime and at least one drink in the past year.

[12] Looking at these numbers disaggregated by race, we find in our sample that 61% of the white respondents ever drink alcoholic beverages and 43% of the African American. This also match the numbers of the National Center for Health Statistics which report 59% and 40% of current drinkers for white and African American respectively.

[13] For the first three waves (1999, 2001 and 2003), people are asked how many drinks they have

Table 3.3: Health Behaviors Summary Statistics

Variable	Mean	Std. Dev.	#Person-Years
Smoking Status			42836
Current Smoker	0.183	0.387	
Cigarette Consumption			7743
Smokes 1 to 9 cig/day	0.335	0.472	
Smokes 10 to 19 cig/day	0.360	0.480	
Smokes 20 or more cig/day	0.305	0.460	
Alcohol			42820
Drinks Alcohol	0.527	0.499	
Frequency of Alcohol Consumption[1]			26012
Never drinks	0.459	0.498	
Less than 1 drink per month	0.157	0.364	
One drink per month	0.112	0.316	
Several drinks per month	0.085	0.279	
One drink per week	0.091	0.288	
Several drinks per week	0.073	0.260	
Drinks everyday	0.022	0.147	
Exercise			42624
Never	0.162	0.368	
1 or 2 times/week	0.181	0.385	
3 to 6 times/week	0.294	0.456	
7 times/week	0.326	0.469	
8 to 14 times/week	0.016	0.125	
More than 14 times/week	0.021	0.143	

[1] This only considers waves 2005, 2007, 2009, and 2011.

only for the four last waves (2005, 2007, 2009 and 2011).[14]

Table 3.4 presents details about respondents with breast cancer. Individuals in

Table 3.4: Descriptive Statistics for Individuals with Breast Cancer

Variable	Mean	Std. Dev.	# Person-Years
Years Since BC Diagnosis	11.441	12.155	873
Age at BC Diagnosis	50.507	14.997	889
Currently[1]			
Cured	0.695	0.461	491
In Remission	0.189	0.392	491
In Treatment	0.116	0.321	491

[1] These questions are asked starting only in 2005.

the sample responded to the following question: “Has a doctor ever told you that you

on average per day: “In the last year, on average, how often did you have any alcohol to drink? Would you say, less than one a month, about once a month, several times a month, about once a week, several times a week, or every day?”. For the four last waves , the categories were changed and the questions about daily consumption referred to *days when respondents drink*: “In the last year, on the days you drank, about how many drinks did you have?”.

[14] In later regressions, we also only use data from years 2005, 2007, 2009 and 2011, when looking at alcohol behaviors.

have or had cancer or a malignant tumor?". If the respondent answers yes, follow-up questions were asked regarding the type of cancer and the stage. The majority of our respondents are "cured"[15] while approximately 12% are in treatment.[16] As can be seen in Table 3.4, the sample average age for a breast cancer diagnosis is approximately 50. However, it is important to consider that there is a censoring issue in these data in the sense that they do not contain information on respondents who were no longer alive at the survey date. The concern is that individuals with cancer who have not succumbed to the disease may not be representative of those who are diagnosed. In particular, there are two main sources of bias.

First, as mentioned, we observe someone with cancer only if they are still alive. If this were the only source of bias, then the data would contain women who are on average older. Indeed, women who are diagnosed at younger ages have a higher mortality rate. Specifically, women diagnosed between 25 and 29 years old have an overall 5-year relative survival rate of approximately 72%. This rate increases to 80% for women diagnosed between 35 and 39 years old, and to $84\% - 86\%$ for women aged between 45 and 80 years at their diagnosis (Anders et al., 2009). Further, the longer people have lived with breast cancer, the lower is the probability they will die from breast cancer. For example, the 5-year relative survival probability is between 80 and 90% at the time of the diagnostic for local and regional breast cancers.[17] It increases to between 85 and 96% after 5 years survived since the diagnosis for these same types of cancer (Merrill and Hunter, 2010). Therefore, this source of censoring leads to data that contains an upward bias in the average years of survival.

Second, obviously we observe someone with cancer in the data only if they have been diagnosed prior to the time of the survey. Since some women in the sample without cancer will be diagnosed in the future, the mean reported age of diagnosis is lower.[18] According to Breastcancer.org, a twenty year old woman has a 0.06% probability of developing invasive breast cancer in the next 10 years. This probability increases as the woman ages: it is equal to 2.31% for women of age 50 and 3.84% for women of age 70. In our sample, although a woman does not report having breast cancer at the time of the survey, this does not imply she will not develop breast cancer in the future.

In Table 3.5, we report prevalence of breast cancer diagnosis by demographic groups.[19] The proportion of respondents having breast cancer is larger among whites than among individuals of other races. This is in line with national statistics, which

[15] Cancers is considered as "cured" when doctors cannot detect cancer five years after diagnosis (American Cancer Society, 2006).

[16] Questions about whether the respondent is currently in treatment, in remission, or has been cured are asked only starting in 2005. The sample size is therefore smaller.

[17] In our data set, we cannot tell the stage at diagnosis of the cancer. But local and regional stages are the most common stages (Merrill and Hunter, 2010).

[18] See appendix for more details.

[19] There are some women in the sample who have breast cancer but have not yet been diagnosed. Diagnosis requires going to the doctor and women without adequate insurance are going to be less likely to go to the doctor. However, given that the woman does not know she has breast cancer this will not influence our results.

Table 3.5: Proportion of Breast Cancer Diagnoses Disaggregated by Demographics

	Proportion of Breast Cancer Diagnoses			
Variable	**Mean**	**Std. Dev.**	**Person-Years**	**p-value**[1]
Race				0.000***
White	0.025	0.156	24814	
Black	0.016	0.126	13166	
Other	0.012	0.107	4895	
Age				0.000***
Younger than 30	0.000	0.019	8643	
Between 30 and 59	0.016	0.126	27012	
60 and older	0.062	0.242	7220	
Family Composition				0.000***
Have Children	0.023	0.149	34732	
Childless	0.012	0.110	8143	
Age at First Child				0.034*
Younger than 35	0.023	0.150	33444	
35 and older	0.016	0.124	1288	
Education				0.042*
No Degree School	0.023	0.150	7372	
High School	0.022	0.147	17800	
Associate or Bachelor	0.018	0.135	13955	
>Bachelor	0.018	0.134	3748	
Family Income				0.000***
<20,000$	0.029	0.168	8404	
≥20,000$ & <50,000$	0.016	0.127	10578	
>50,000$	0.020	0.139	23893	

[1] The reported p-values are from multivariate tests on equal means.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 3.6: Proportion of Breast Cancer Diagnoses Disaggregated by Health Behaviors

	Proportion of Breast Cancer Diagnoses			
Variable	**Mean**	**Std. Dev.**	**Person-Years**	**p-value**[1]
Smoking Status				0.000***
Current Smoker	0.014	0.116	7852	
Former Smoker	0.036	0.186	9026	
Never Smoked	0.018	0.132	25929	
Cigarette Consumption				0.037*
Smokes 1 to 9 cig/day	0.010	0.102	2592	
Smokes 10 to 19 cig/day	0.012	0.108	2789	
Smokes 20 or more cig/day	0.019	0.137	2362	
Alcohol				0.000***
Drinks Alcohol	0.018	0.133	22561	
Never Drinks Alcohol	0.024	0.152	20259	
Frequency of Alcohol Consumption[2]				0.058
Less than 1 drink per month	0.019	0.135	4082	
One drink per month	0.017	0.128	2920	
Several drinks per month	0.014	0.117	2221	
One drink per week	0.017	0.129	2376	
Several drinks per week	0.025	0.157	1894	
Drinks everyday	0.031	0.174	574	
Exercise				0.000***
Never	0.032	0.177	6901	
1 or 2 times/week	0.019	0.135	7710	
3 to 6 times/week	0.019	0.136	12550	
7 times/week	0.018	0.134	13896	
8 to 14 times/week	0.012	0.108	673	
More than 14 times/week	0.020	0.141	894	

[1] The reported p-values are from multivariate tests on equal means.

[2] This only considers waves 2005, 2007, 2009 and 2011.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

indicate that white women have the highest risk of getting breast cancer (American Cancer Society, 2005). Childless women and women whose first birth is after age 35 have an increased risk of developing breast cancer (Britt et al., 2007), which is also reflected in our data. However, conditional on having children, the proportion of breast cancer patients is larger for women who had their child at 35 years old or later. This is consistent with the fact that a higher age at first full-term pregnancy is considered as a risk factor for breast cancer (for example, Kelsey, 1993).

Next we examine relationships between risky health behaviors and breast cancer prevalence. Table 3.6 displays breast cancer diagnosis among individuals with differing smoking, drinking, and exercise habits. The first few rows show that the proportion of breast cancer patients is the largest among former smokers. Among smokers, breast cancer prevalence is the highest for respondents who smoke more than 19 cigarettes per day.

Regarding alcohol consumption behaviors, prevalence is lower in the group of respondents who do drink alcohol. Among those who drink, breast cancer prevalence is the highest for individuals who drink everyday.[20]

The bottom panel of table 3.6 presents statistics for physical activity. The respondents were asked about weekly exercise frequency for heavy and light workouts.[21] Specifically, they were asked "How often do you participate in vigorous/light physical activity or sports." A problem with this wording is that there is no information about the measure of time spent by a person doing physical activity.[22] In our analysis, we first regroup light and heavy physical activities into one variable called "exercise." Secondly, we define the following six categories: no exercise (neither light nor heavy), exercise one to two times a week, exercise three to six times a week, exercise seven times a week, exercise eight to fourteen times a week, and exercise more than fourteen times a week.[23] The proportion of breast cancer patients is the largest among people who never exercise, while it is the lowest among people who exercise between 8 and 14 times per week. The main point that emerges from table 3.6 is that breast cancer incidence differs with the degree an individual engages in various lifestyle behaviors. In the next sections, we examine this in more detail.

3.3 Model

As we discussed in the Section 3.1, many papers in the medical literature examine the influence of lifestyle behaviors on breast cancer diagnosis and outcomes. In this section, we present a model that links breast cancer diagnosis to lifestyle choices. In our framework, a women (indexed by i) makes a lifestyle choice (indexed by l) in each period (indexed by t), where the lifestyle behaviors may be influenced by breast cancer diagnosis. The lifestyle choices concern how much to smoke, how much to consume alcohol, and how much to engage in physical activity. Let y^*_{ilt} be a latent variable measuring the continuous quantity of lifestyle activity l chosen by individual i at time t. Specifically, the baseline model is given by

$$y^*_{ilt} = 1\left(y^*_{ilt-1} > 0\right)\alpha_l + b_{it}\delta_l + X_{it}\beta_l + \mu_{il} + \varepsilon_{ilt}, \tag{3.1}$$

where b_{it} is a binary indicator for whether i is diagnosed with breast cancer at time t, μ_{il} is a person/behavior-specific random effect, and ε_{ilt} is an idiosyncratic effect. The X_{it} vector includes explanatory person-specific variables such i's age, her marital status, whether she has children, her income, and her education level. Lifestyle choices

[20] As the survey questions concerning alcohol consumption were not consistently worded across waves, we report statistics only for the four last waves (2005, 2007, 2009 and 2011).

[21] Specifically, heavy exercise refers to "heavy housework, aerobics, running, swimming, bicycling or similar that causes heavy sweating or large increases in breathing or heart rate" (PSID, 2005). Light exercise includes "walking, dancing, gardening, golfing, bowling or similar that causes only light sweating or slight to moderate increases in breathing or heart rate" (PSID, 2005).

[22] See the discussion in Berniell et al. (2013).

[23] Further, some persons report extreme values which could indicate some misunderstanding of the question.

exhibit persistence, which may be due to addiction (such as smoking and drinking alcohol) or to habit persistence (such as exercise).[24] Therefore, we allow individual i's lifestyle choices at time t to depend on whether she participated in that behavior in the immediate past $1(y^*_{ilt-1} > 0)$.

We should note that each behavior is reported in the data as a bracketed variable. We define $m = 1$ as not participating in the activity and let the quantity of activity increase as m increases where

$$y_{ilt} = m \text{ iff } \kappa_{lm} \leq y^*_{ilt} < \kappa_{lm+1}, \;\; m = 1, 2, .., M_l.$$

Assume that $\kappa_{l1} = -\infty$, $\kappa_{l2} = 0$, and $\kappa_{lM_l+1} = \infty$.

Given that lifestyle choices are persistent, we estimate this model using a panel dataset. To control for endogenous initial conditions (à la Heckman, 1981), we specify the initial period values

$$y^*_{il0} = C_i\lambda_l + b_{i0}\delta_l + X_{i0}\beta_l + \mu_{il} + \varepsilon_{il0}, \tag{3.2}$$

$$\varepsilon_{ilt}|(\overline{X}_i, y_{il,t-1}, ...y_{il0}, \mu_{il}) \sim N(0, \sigma^2_\varepsilon), \tag{3.3}$$

where $\overline{X}_i$ denotes the mean over time of the explanatory variables (excluding the year fixed effects) and C_i is a set of variables affecting only initial choices. For smoking behaviors, these include age when i started smoking.[25] Unfortunately, the PSID does not contain any information on the age at which respondents started drinking or exercising. For these lifestyle choices, we include the level of drinking or exercising behavior observed in the first period of the data as an initial condition. In this approach, there may be a concern about the initial value of y_{il0}. One possibility is to treat it as nonrandom, which would imply that μ_{il} and y_{il0} are independent. However, μ_{il} and y_{il0} may not be independent, so we follow Wooldridge (2005) that builds on Chamberlain (1984) and specify the density of the fixed effect conditional on the initial condition as

$$\mu_{il} = \gamma_0 + \gamma_1 y_{il0} + \overline{X}_i\gamma_2 + a_{il}, \;\; a_{il}|\left(y_{il0}, \overline{X}_i\right) \sim N(0, \sigma^2_a). \tag{3.4}$$

As discussed in Wooldridge (2005), the fixed effects can then be integrated out to yield the likelihood function of the random effects Probit model with time-t, observation-i explanatory variables: $(X_{it}, y_{il,t-1}, ...y_{il0}, \overline{X}_i)$.

[24] Economists do not distinguish between habit-formation and addiction; both are modeled as consumption decisions today affecting the utility function in the future.

[25] For those who do not smoke, the initial condition is set to zero.

3.4 Estimation Methodology

We first discuss the estimation methodology treating the three models corresponding to the three activities of interest separately. Using equation (3.1), define

$$\begin{aligned} Y_{ilt}(\mu_i) &= y^*_{ilt} - \varepsilon_{ilt} \\ &= 1\left(y^*_{ilt-1} > 0\right)\alpha_l + b_{it}\delta_l + X_{it}\beta_l + \mu_{il} \end{aligned}$$

as the deterministic part of y^*_{ilt} after conditioning on μ_{il} for $t \geq 1$, and, using equation (3.2), define

$$Y_{il0}(\mu_i) = y^*_{il0} - \varepsilon_{il0}.$$

The vector of parameters to estimate for model l is $\theta = (\alpha_l, \delta_l, \beta_l, \sigma_{el}, \kappa_l, \lambda_l)$, and the log likelihood contribution for i is

$$L_{il} = \log \int \left[\prod_{t=0}^{T} \prod_{m=1}^{M_l} \Delta_{ilm}(\mu_{il})^{1(y_{ilt}=m)} \, d\Phi(\mu_{il}) \right]$$

$$\Delta_{ilm}(\mu_{il}) = \Phi\left[\kappa_{lm+1} - Y_{ilt}(\mu_{il})\right] - \Phi\left[\kappa_{lm} - Y_{ilt}(\mu_{il})\right].$$

The log likelihood function $L_l = \sum_i L_{il}$ can be maximized in Stata using a straightforward quadrature method (Butler and Moffitt, 1982), while more complex error structures probably would require use of simulation methods (Stern, 1997).

One might be concerned that the inclusion of the random effect μ_{il} in equations (3.1) and (3.2) does not sufficiently capture variation that would be incorporated with a richer covariance structure across time, behaviors, and/or individuals. For example, defining

$$\begin{aligned} V_{ilt} &= 1\left(y^*_{ilt-1} > 0\right)\alpha_l + b_{it}\delta_{l1} + b_{it}(1-b_{it})\delta_{l2} \\ &\quad + b_{it}(1-b_{it})\,1\left(y^*_{ilt-1} > 0\right)\delta_{l3} + X_{it}\beta_l \end{aligned}$$

as the non-random part of equation (3.1), a much more flexible error structure would be represented as

$$\begin{aligned} y^*_{ilt} &= V_{ilt} + u_{lt} + \mu_{il} + \varepsilon_{ilt}, \\ u_t &\sim iidN(0, \Omega_u), \\ \mu_i &\sim iidN(0, \Omega_\mu), \\ \varepsilon_{it} &\sim iidN(0, \Omega_\varepsilon) \end{aligned} \tag{3.5}$$

(with appropriate identifying conditions on covariance matrices) or

$$\begin{aligned} y^*_{ilt} &= 1\left(y^*_{ilt-1} > 0\right)\alpha_l + b_{it}\delta_{l1} + b_{it}(1-b_{it})\delta_{l2} \\ &\quad + b_{it}(1-b_{it})\,1\left(y^*_{ilt-1} > 0\right)\delta_{l3} + X_{it}\beta_l + \sum_{k=1}^{K_\xi}\varphi^\xi_{lk}\xi_k + \sum_{k=1}^{K_\zeta}\varphi^\zeta_{lk}\zeta_{il} + \varepsilon_{ilt} \end{aligned} \tag{3.6}$$

where $(\varphi^{\xi}, \varphi^{\zeta})$ are factor loadings associated with factors (ξ, ζ) (e.g., Heckman, Stixrud, and Urzúa, 2006; Conti, Heckman, and Urzúa, 2010; Dean et al., 2015, 2016) or a specification that emphasizes more general forms of serial correlation. While the parameters of any such structure could be estimated using simulation methods (e.g., Dean et al., 2015, 2016), they would still be significantly more expensive to estimate.

Alternatively, one could estimate the model in equations (3.1) and (3.2), and then test for more sophisticated error structures using Pseudo-Lagrange Multiplier tests (e.g., Checkovich and Stern, 2002; Friedberg and Stern 2014; Dean et al., 2016). Details are provided in the appendix.

3.5 Results

We estimate three random-effects ordered probit models and our results indicate that breast cancer diagnosis (and recency) of diagnosis impacts lifestyle choices. However, the impact of diagnosis has a different effect on smoking, drinking, and exercising behavior and the impact also depends upon the recency of the diagnosis.

We first start by discussing the impact of breast cancer diagnosis on smoking behavior. We consider four categories of daily smoking intensity: (i) does not smoke, (ii) smokes fewer than 10 cigarettes a day; (iii) smokes between 10 and 19 cigarettes a day, (iv) smokes more than 20 daily, which is more than a pack of cigarettes. Table 3.7 presents random-effects ordered probit estimates where the explanatory variables include smoking behavior in the previous year, demographics, as well as breast cancer variables. The first two columns of Table 3.7 indicate that whether an individual has been diagnosed with breast cancer has no significant impact on smoking behavior conditional on past behavior and demographic variables. Column (2) includes controls for initial conditions as outlined in Section 3.3. However, as columns (3) and (4) indicate, if the woman was diagnosed with breast cancer less than five years ago she will significantly decrease her smoking behavior (-0.289) where this effect is robust to including initial conditions (column (4),-0.326). The differential impact of the time of diagnosis on smoking behavior could arise from a few sources. First, the individual may react to a diagnosis by curbing unhealthy habits such as smoking, but this effect may deteriorate over time as the individual survives past the initial stages. Second, the woman may be undergoing treatment which makes smoking more difficult in the short run due to lack of energy, for example.

The signs and significance of the control variables are intuitive and in-line with results from other studies. First, past smokers are more likely to be current smokers and the significant positive effect persists after controlling for unobserved heterogeneity (in columns (2) and (4)). Our finding is consistent with numerous studies that have shown that smoking exhibits true state dependence (i.e., the effect is significant after controlling for unobserved heterogeneity). Our results indicate white individuals smoke more than black individuals. We also find that married individuals smoke less than those who are not married as do women with a higher education relative to other education categories. Finally, we find that individuals with lower incomes

Table 3.7: Random Effects Ordered Probit Regressions for Smoking

Dependent Variable: Ordered Variable for Number of Cigarettes Smoked				
	(1)	(2)	(3)	(4)
Lagged Behavior				
Smoker Last Period	2.432***	1.646***	2.433***	1.648***
	(0.030)	(0.045)	(0.030)	(0.045)
Breast Cancer Variables				
Diagnosed with Breast Cancer	-0.096	-0.150		
	(0.098)	(0.142)		
Recent Breast Cancer Diagnosis			-0.289*	-0.326+
			(0.140)	(0.171)
Other Controls				
Age				
Aged in 30s, 40s, or 50s	-0.028	0.172***	-0.027	0.172***
	(0.033)	(0.051)	(0.033)	(0.051)
Aged 60 or Older	-0.519***	-0.160	-0.520***	-0.164
	(0.051)	(0.103)	(0.051)	(0.103)
Race				
White	0.474***	0.701***	0.473***	0.700***
	(0.053)	(0.084)	(0.053)	(0.084)
Black	0.081	0.196*	0.080	0.195*
	(0.055)	(0.088)	(0.055)	(0.088)
Family Situation				
Married	-0.227***	-0.259***	-0.227***	-0.259***
	(0.030)	(0.039)	(0.030)	(0.039)
Have Children	0.004	-0.032	0.004	-0.032
	(0.042)	(0.063)	(0.042)	(0.063)
Highest Education				
High School	-0.241***	-0.352***	-0.241***	-0.352***
	(0.036)	(0.052)	(0.036)	(0.052)
University Degree	-0.505***	-0.700***	-0.505***	-0.700***
	(0.042)	(0.061)	(0.042)	(0.060)
Post Graduate	-0.896***	-1.268***	-0.895***	-1.266***
	(0.075)	(0.107)	(0.075)	(0.107)
Income				
Less than 20K	0.102**	0.109**	0.102**	0.109**
	(0.035)	(0.042)	(0.035)	(0.042)
Between 20 and 50K	0.095**	0.106**	0.095**	0.105**
	(0.031)	(0.038)	(0.031)	(0.038)
Initial Conditions Included	no	yes	no	yes
Number of Observation	33,967	33,942	33,967	33,942
Number of Individuals	8,019	8,010	8,019	8,010

Standard errors in parentheses + $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All regressions include cutt off points, individual heterogeneity variance and year fixed effects.

The initial conditions specifications inlcude the mean over time of all time varying regressors.

(under $50,000\$$) smoke more than higher income women.

Table 3.8 presents the results of a random effects ordered probit regression for number of alcoholic drinks, where the dependent variable is ordered according to: (i) non-drinker, (ii) women who have on average drink at most once a week, and (iii) women who on average drink more than one time a week. As with smoking, our results indicate that past drinking behavior is a positive significant indicator of current drinking behavior, and this effect remains after controlling for initial conditions in columns (2) and (4). However, in contrast to smoking behavior women do not change their alcohol consumption after a breast cancer diagnosis regardless of when the diagnosis was made.

The control variables indicate that women aged 60 or older drink less, but that white women drink more than black women. In addition, we find that married individuals drink less often, as do those with children. Finally, drinking more often is more likely among those with higher education relative to other groups and among those with a larger income.

We present the results of the random-effects ordered probit for exercise frequency in Table 3.9. Exercise frequency is based on number of exercise sessions per week as discussed in Section 3.2 where the categories are number of times per week participate in exercise (i) no times, (ii) 1-2 times, (iii) 3-6 times, (iv), 7 times, (v) 6-14 times, and (vi) more than 14 times. As the results in columns (1) and (2) show a diagnosis of breast cancer significantly impacts the amount of exercise in a negative way. Perhaps this result is not so surprising given that women often undergo treatment after a breast cancer diagnosis that can weaken them and make it more difficult to engage in extra physical activity. The results in columns (3) and (4) show that women also decrease their amount of physical activity after a recent diagnosis, which is not surprising.

The other control variables indicate that the older the woman is the less physical activity she participates in. The results also show that being white is associated with higher levels of physical activity. We also find married women engage in more physical activity as well relative to non-married women. Furthermore, the higher the level of education the woman has the more she engages in weekly physical activity. Finally, individuals with income less than \$20,000 engage in less exercise relative to individuals with income between \$20,000 and \$50,000.

3.6 Conclusions

According to the National Breast Cancer Foundation, one in eight US women are impacted by breast cancer.[26] We use longitudinal data from the PSID, starting from 1999 to 2011, to examine to what extent women who are diagnosed with breast cancer change their (potentially risky) lifestyle choices. We find that women who were

[26] http://www.nationalbreastcancer.org/about-breast-cancer/?utm_campaign=Grants%20Education&utm_sourc 9xAqvrVuqQuEIE-ewB6XWqWwWdTDxoCMK3w_wcB
Referenced on October 28, 2016

Table 3.8: Random Effects Ordered Probit Regressions for Alcohol Consumption

Dependent variable: Ordered Variable for Number of Alcoholic Drinks	(1)	(2)	(3)	(4)
Lagged Behavior				
Number of Drinks Last Period	0.220***	0.051***	0.220***	0.051***
	(0.011)	(0.012)	(0.011)	(0.012)
Breast Cancer Variables				
Diagnosed with Breast Cancer	-0.079	-0.101		
	(0.136)	(0.142)		
Recent Breast Cancer Diagnosis			-0.011	-0.087
			(0.180)	(0.186)
Other Controls				
Age				
Aged in 30s, 40s, or 50s	0.013	0.104*	0.0116	0.103*
	(0.048)	(0.050)	(0.048)	(0.050)
Aged 60 or Older	-0.394***	-0.163*	-0.398***	-0.167*
	(0.067)	(0.070)	(0.067)	(0.070)
Race				
White	0.849***	0.716***	0.848***	0.715***
	(0.074)	(0.076)	(0.074)	(0.076)
Black	0.137^+	0.148^+	0.136^+	0.148^+
	(0.078)	(0.081)	(0.078)	(0.081)
Family Situation				
Married	-0.192***	-0.151***	-0.192***	-0.151***
	(0.043)	(0.044)	(0.043)	(0.044)
Have Children	-0.474***	-0.391***	-0.474***	-0.391***
	(0.059)	(0.061)	(0.059)	(0.061)
Highest Education				
High School	0.465***	0.467***	0.465***	0.467***
	(0.061)	(0.063)	(0.061)	(0.063)
University Degree	0.804***	0.802***	0.804***	0.802***
	(0.064)	(0.067)	(0.064)	(0.067)
Post Graduate	1.008***	1.017***	1.009***	1.017***
	(0.082)	(0.085)	(0.082)	(0.085)
Income				
Less than 20K	-0.072	-0.056	-0.072	-0.056
	(0.045)	(0.047)	(0.045)	(0.047)
Between 20 and 50K	-0.062	-0.061	-0.061	-0.061
	(0.039)	(0.040)	(0.039)	(0.040)
Initial Conditions Included	no	yes	no	yes
Number of Observations	18,082	18,036	18,082	18,036
Number of Individuals	7,175	7,147	7,175	7,147

Standard errors in parentheses, $^+$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All regressions include cut off points, individual heterogeneity variance, and year fixed effects.

The initial conditions specifications include the mean over time of all time varying regressors.

Table 3.9: Random Effects Ordered Probit Regressions for Exercising

Dependent Variable: Ordered Variable for Exercise Frequency				
	(1)	(2)	(3)	(4)
Lagged Behavior				
Exercise Frequency Last Period	0.173***	0.126***	0.174***	0.126***
	(0.007)	(0.007)	(0.007)	(0.007)
Breast Cancer Variables				
Diagnosed with Breast Cancer	-0.144**	-0.167**		
	(0.051)	(0.052)		
Recent Breast Cancer Diagnosis			-0.138*	-0.156*
			(0.0698)	(0.0705)
Other Controls Age				
Aged in 30s, 40s, or 50s	-0.134***	-0.147***	-0.135***	-0.148***
	(0.019)	(0.020)	(0.019)	(0.020)
Aged 60 or Older	-0.381***	-0.392***	-0.386***	-0.399***
	(0.026)	(0.026)	(0.026)	(0.026)
Race				
White	0.155***	0.134***	0.154***	0.133***
	(0.026)	(0.026)	(0.026)	(0.026)
Black	-0.062*	-0.066*	-0.063*	-0.067*
	(0.027)	(0.028)	(0.027)	(0.028)
Family Situation				
Married	0.055**	0.057***	0.055**	0.056***
	(0.017)	(0.017)	(0.017)	(0.017)
Have Children	0.017	0.017	0.017	0.017
	(0.023)	(0.024)	(0.023)	(0.024)
Highest Education				
High School	0.113***	0.103***	0.113***	0.103***
	(0.022)	(0.023)	(0.022)	(0.023)
University Degree	0.163***	0.154***	0.163***	0.154***
	(0.024)	(0.024)	(0.024)	(0.024)
Post Graduate	0.198***	0.199***	0.198***	0.199***
	(0.032)	(0.033)	(0.032)	(0.033)
Income				
Less than 20K	0.048*	0.039+	0.048*	0.039+
	(0.020)	(0.020)	(0.020)	(0.020)
Between 20 and 50K	0.064***	0.057**	0.064***	0.057**
	(0.017)	(0.018)	(0.017)	(0.018)
Initial Conditions Included	no	yes	no	yes
Number of Observations	33,851	33,851	33,851	33,851
Number of Individuals	8,009	8,009	8,009	8,009

Standard errors in parentheses, $^{+}$ $p < 0.10$, * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

All regressions include cut off points, individual heterogeneity variance and year fixed effects.

The initial conditions specifications include the mean over time of all time varying regressors.

recently diagnosed with breast cancer smoke less, which some research has shown is a contributing factor to breast cancer. In contrast to smoking behavior women do not change their alcohol consumption after a breast cancer diagnosis regardless of when the diagnosis was made. Furthermore, a diagnosis of breast cancer significantly impacts the amount of exercise in a negative way. Perhaps this result is not so surprising given that women often undergo treatment after a breast cancer diagnosis that can weaken them and make it more difficult to engage in extra physical activity. Our findings allow us to learn more about the trade-offs women are willing to make between participating in unhealthy (but enjoyable) habits and increasing one's life expectancy.

Acknowledgment

Thanks to the seminar participants at the iHEA 10th World Congress in Dublin for their comments. We gratefully acknowledge support from the Swiss National Science Foundation Grant Number 100018_130333. The collection of data used in this study was partly supported by the National Institutes of Health under grant number R01 HD069609 and the National Science Foundation under award number 1157698.

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Appendix

Lagrange Multiplier Tests

Consider the alternative model in equation (3.5). It's log likelihood contribution for family n is

$$L_n = \log \int \left[\prod_i \prod_{t=0}^{T} \Lambda_{nit}(\upsilon_n) \, dF(\upsilon_n) \right] \tag{3.7}$$

where

$$\upsilon_n = (u_n', e_n')'$$

is the $N_n \times 1$ vector of unobserved heterogeneity errors, $N_n = L(1 + \iota_n)$, $F(\upsilon_n)$ is its joint distribution function,

$$\begin{aligned} \Lambda_{nit}(\upsilon_n) &= \int \cdots \int \prod_l 1\left(\kappa_{ly_{nilt}} \leq y^*_{nilt}(\upsilon_n) < \kappa_{ly_{nilt}+1}\right) dG(\varepsilon_{nit}) \\ &= \int_{\kappa_{ly_{ni1t}} - W_{ni1t}(\upsilon_n)}^{\kappa_{ly_{ni1t}+1} - W_{ni1t}(\upsilon_n)} \cdots \int_{\kappa_{ly_{niLt}} - W_{niLt}(\upsilon_n)}^{\kappa_{ly_{niLt}+1} - W_{niLt}(\upsilon_n)} dG(\varepsilon_{nit}), \end{aligned}$$

$$W_{nilt}(\upsilon_n) = V_{nilt} + u_{nl} + e_{nil},$$

and $G(\varepsilon_{nit})$ is the joint distribution of ε_{nit}. Since we can write the log likelihood, we can perform a Lagrange Multiplier test (Breusch and Pagan, 1982). However, the score statistics with respect to Ω_u, Ω_e, and Ω_ε are quite complicated and would not easily be produced by Stata.[27]

However, we can consider carefully chosen functions of generalized residuals from estimation of equation (3.1) that should behave differently under

$$H_0 : \Omega_u = 0, \Omega_e = \begin{pmatrix} \sigma_{e1} & 0 & \cdots & 0 \\ 0 & \sigma_{e2} & \cdots & 0 \\ \vdots & \vdots & \ddots & \vdots \\ 0 & 0 & \cdots & \sigma_{eL} \end{pmatrix}, \Omega_\varepsilon = I$$

[27] They involve differentiation of multiple integrals where the Choleski decompositions of the covariance matrices are in each of the limits of integrations and the integrand is a L-dimension joint normal density function.

than under its general alternative.

Let

$$\begin{aligned}
\underset{T\times 1}{r_{nil}} &= E\varepsilon_{nil} \mid y_{nil} \\
&= E_e \left[E\varepsilon_{nil} \mid \kappa_{ly_{nilt}} - (V_{nilt} + e_{nil}) \leq \varepsilon_{nilt} < \kappa_{ly_{nilt}+1} - (V_{nilt} + e_{nil}) \right] \\
&= E_e \left[\frac{\phi\left[\kappa_{ly_{nilt}+1} - (V_{nilt} + e_{nil})\right] - \phi\left[\kappa_{ly_{nilt}} - (V_{nilt} + e_{nil})\right]}{\Phi\left[\kappa_{ly_{nilt}+1} - (V_{nilt} + e_{nil})\right] - \Phi\left[\kappa_{ly_{nilt}} - (V_{nilt} + e_{nil})\right]} \right]
\end{aligned}$$

be the vector of generalized residuals for i associated with the T choices over behavior l. These residuals can be simulated as

$$\widetilde{r}_{nil} = \frac{1}{2K} \sum_{k=1}^{K} \sum_{a=-1,1} R\left(a e_{nil}^{k}\right)$$

where

$$R(e) = \frac{\phi\left[\kappa_{ly_{nilt}+1} - (V_{nilt} + e)\right] - \phi\left[\kappa_{ly_{nilt}} - (V_{nilt} + e)\right]}{\Phi\left[\kappa_{ly_{nilt}+1} - (V_{nilt} + e)\right] - \Phi\left[\kappa_{ly_{nilt}} - (V_{nilt} + e)\right]}$$

and e_{nil}^{k} is a draw from its estimated density. Consider

$$S_{u1} = \sum_{l} \left| \sum_{n} \sum_{i} \sum_{j \neq i} \overline{r}_{nil} \overline{r}_{njl} \right|$$

or

$$S_{u2} = \sum_{l} \sum_{k} \left| \sum_{n} \sum_{i} \sum_{j \neq i} \overline{r}_{nil} \overline{r}_{njk} \right|$$

where

$$\overline{r}_{nil} = \frac{1}{T} \sum_{t} \widetilde{r}_{nilt}$$

If $\Omega_u = 0$, then, since family members are behaving independently, S_{u1} and S_{u2} should be close to 0, while, if $\Omega_u \neq 0$, then both should deviate from 0. S_{u1} should have power against the diagonal elements of Ω_u deviating from 0 but not off-diagonal elements deviating from 0, while S_{u2} should have power against the general alternative. Next, consider

$$S_e = \sum_{l} \sum_{j \neq l} \left| \sum_{n} \sum_{i} \overline{r}_{nil} \overline{r}_{nij} \right|.$$

If Ω_e is diagonal, then, since individual/behavior effects are independent, S_e should be close to 0, while, if Ω_e is not diagonal, then S_e should deviate from 0. Finally, consider

$$S_\varepsilon = \sum_{l} \sum_{n} \sum_{i} \widetilde{r}_{nil}' \widetilde{r}_{nil}$$

If $\Omega_\varepsilon = I$, then, since idiosyncratic effects are independent, S_ε should be close to

0, while, if $\Omega_\varepsilon \neq I$, then S_e should deviate from 0. One can easily simulate the distribution of each statistic under H_0 to pick critical values for each test.

The same set of test statistics can be used for the model in equation (3.6). This is so because the extra errors in the specification imply the same correlations across family members and behaviors. In fact the model in equation (3.6) can be written the form of equation (3.5).

Age at diagnosis

Let a_{it} be the age of i in year t. What is reported in the data is

$$\frac{\int_{t-a_t}^{t} (a_t - t + s)\, S(t-s)\, f(a_t - t + s)\, ds}{\int_{t-a_t}^{t} S(t-s)\, f(a_t - t + s)\, ds}$$

where $f(\cdot)$ is the density of the age of cancer diagnosis (conditional on being diagnosed) and $S(\cdot)$ is the survivor function from day of diagnosis. What you report it says (and what you would like it to say) is

$$\int_0^\infty s f(s)\, ds. \tag{3.8}$$

There are two main sources of bias:

1. In the data, we observe someone with cancer only if they are still alive; thus the inclusion of $S(\cdot)$. If this were the only source of bias, then we would overestimate the average age because women who were diagnosed at a young age had a smaller chance of being alive at t.

2. In the data, we observe someone with cancer only if they have been diagnosed prior to their age at t. Since some women in the sample without cancer will be diagnosed in the future, the effect of this effect lowers the mean reported age of diagnosis.

One might want to estimate the object in equation (3.8) using our data $\{a_i, c_i, b_i\}_i$ where a_i is sample person i's age, c_i is an indicator for whether she has cancer, and b_i is the age she was diagnosed if $c_i = 1$. Given an estimate $\widehat{S}(\cdot)$ of the survivor function from some other source, one could estimate $f(\cdot)$ (or parameters associated with a parametric assumption about the form of $f(\cdot)$) by maximizing the log likelihood function,

$$L = \sum_i c_i \log\left(\frac{f(b_i)\,\widehat{S}(a_i - b_i)}{\int f(b)\,\widehat{S}(a_i - b)\, db}\right) + (1 - c_i)\log(1 - F(a_i))$$

where $F(\cdot)$ is the distribution function associated with density $f(\cdot)$. One might want to generalize by conditioning $f(\cdot)$ on a reasonable (and small) set of exogenous covariates.

Marginal Effects

We follow Stern (1991) to compute the marginal effects of the parameter estimates. Specifically, let

$$g(y_i^*) = x_i\beta + u_i$$

where $g(\cdot)$ is a monotone-increasing function, $g(y_i^*)$ is a latent measure of some outcome variable, and $u_i \sim iidN(0,1)$. Assume that

$$y_i = \kappa_k \text{ iff } c_k \leq y_i^* < c_{k+1}$$

for $k = 0, 1, .., K+1$. Define $\tau_0 = -\infty$, $\tau_1 = 0$, $\tau_{K+1} = \infty$, and $\tau_k = g(c_k)$ for $k = 2, 3, ..$,K. Assume that we observe $\{y_i, x_i\}_{i=1}^n$ and $\{c_k\}_{k=0}^{K+1}$. This model is an ordered probit model with log likelihood function

$$L = \sum_{i=1}^{n}\sum_{k=0}^{K} 1(y_i = \tau_k)\log\left[\Phi(\tau_{k+1} - x_i\beta) - \Phi(\tau_k - x_i\beta)\right],$$

which is maximized over $\theta = (\beta, \tau_2, \tau_3, .., \tau_K)$. The ML estimates are consistent, efficient, and asymptotically normal. The $g(\cdot)$ function is identified only at c_k $\forall k$. We can fit a spline in slopes or a higher-order spline to the points, $\{c_k, \tau_k\}_{k=0}^{K+1}$ in order to translate values of $g(y_i^*) = x_i\beta + u_i$ into units of y_i^*. Also, we can evaluate

$$\begin{aligned}
& E(x_i\beta + u_i \mid \tau_k - x_i\beta \leq u_i < \tau_{k+1} - x_i\beta) \\
= \; & x_i\beta + E(u_i \mid \tau_k - x_i\beta \leq u_i < \tau_{k+1} - x_i\beta) \\
= \; & x_i\beta + \frac{\phi(\tau_{k+1} - x_i\beta) - \phi(\tau_k - x_i\beta)}{\Phi(\tau_{k+1} - x_i\beta) - \Phi(\tau_k - x_i\beta)}
\end{aligned}$$

and then plug into our spline estimate of $g^{-1}(\cdot)$ to “predict” y_i^*.

Chapter 4

Advertising and Life Satisfaction: Cross-National Evidence on One Million Europeans

joint project with Michelle Sovinsky, [1] Eugenio Proto, [2] and Andrew J. Oswald [3]

4.1 Introduction

Advertising plays a prominent role in modern society. Although it is not known how much advertising a typical citizen witnesses, one modern study by Speers et al. (2011) concluded for the United States that on prime-time television the brand names of food, beverages and restaurants appeared approximately 35,000 times in one year. Coca Cola products, for example, were seen 198 times by the average child and 269 times by the average adolescent. These influences appear to be strengthening through time. Another study by Crowling and Poolsombat (2007) has documented a 4-fold increase in real advertising per-capita in the US over 5 decades.

The links between advertising and human well-being are not fully understood. Effects might operate along two broad channels. First, one way to conceive of advertising is as a force for good. Advertising informs. It may therefore promote human welfare by allowing people to make better choices about the right products for them. Second, an alternative way to conceive of advertising is as a force that creates dissatisfaction and stimulates potentially infeasible desires. If correct, that view, which dates back more than 100 years to the writings of Thorstein Veblen (1904), would imply that advertising might reduce net human welfare by unduly raising the con-

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sumption aspirations of human beings. Since Veblen, many writings have worried about the possibility of, and in some cases found small-scale evidence for, negative effects of advertising upon people's well-being (Richins, 1995; Easterlin and Crimmins, 1991; Bagwell and Bernheim, 1996; Sirgy et al., 1998); Dittmar et al., 2014; Frey et al., 2007; Harris et al., 2009), and a large literature exists particularly on the possible detrimental effects upon children (Andreyeva et al., 2011; Borzekowski and Robinson, 2001; Buijzen and Valkenburg, 2003A; Buizjen and Valkenburg, 2003B; Opree et al, 2012).

At the national level, it is not known which of these two forces – one beneficial and one detrimental – is dominant. The current study, which might be viewed as a contribution to the behavioral science of human happiness, is an attempt to address the question. Even the now-large modern literature on the social science of well-being (Easterlin, 2003; Radcliff, 2001; Diener, 2013; Layard , 2005; Dunn et al. , 2008; Clark and Oswald, 1996; Fowler and Christakis, 2008; Graham et al., 2004; Gilbert, 2006; Stone et al, 2010; Steptoe and Wardle, 2011, De Neve and Oswald, 2012) has so far paid no attention to the topic of advertising. A small number of national variables have been shown to influence national well-being in fixed-effects equations. In particular, the generosity of the welfare state and various macroeconomic variables such as unemployment appear to impact national well-being (Di Tella et al., 2001; Di Tella et al., 2003; Radcliff, 2013). The present study examines – and provides evidence of – links between national advertising and national well-being. Using longitudinal information on countries (built up from pooled cross-sectional surveys), it finds that rises and falls in advertising are followed, a small number of years later, by falls and rises in national life-satisfaction. The results thus reveal an inverse connection between advertising levels and the later well-being of nations.

To perform the statistical analysis, we take a sample of slightly over 900,000 randomly sampled European citizens, who report information on their life-satisfaction levels and on many other aspects of themselves and their lives. The data are from repeated surveys, collected annually, for 27 countries from 1980 to 2011. For each nation, and each year, total advertising expenditure levels are also gathered (details are given later in Materials and Methods). We then match one set of data with the other. To adjust in the analysis for possible confounding factors, we use regression analysis, and examines estimates from fixed-effects equations in which the unobservable characteristics of nations can be held constant. Intuitively, this study thus examines how the change in advertising in a country is correlated with the later change in life-satisfaction levels in that country. None of the paper's results depend on elementary cross-sectional regression equations.

4.2 Materials and Methods

For this paper, data are taken from three different sources: the Eurobarometer Survey, ZenithOptimedia, and the World Bank. The Eurobarometer survey, which began in 1972, is a set of public opinion surveys conducted on behalf of the European Commission. Each spring and autumn, face-to-face interviews are conducted for a new sample of residents of European Union (EU) Member States (around 1000 per country). The questions that respondents are asked are varied and include items intended to assess life satisfaction, to elicit opinions about the state of politics in Europe, to gain insight into perceptions of political institutions, etc. The data recorded in the Eurobarometer are used by the European Commission to monitor the evolution of public opinion and ultimately to aid in decision making.

For this study, data are gathered from individuals from 27 countries over the years 1980 to 2011. Specifically, data are available on the following transition European countries[4]: Bulgaria, Czech Republic, Estonia, Croatia, Hungary, Latvia, Lithuania, Poland, Romania, Slovenia, Slovakia, and Turkey, and on the following non-transition countries: Austria, Belgium, Germany, Denmark, Spain, Finland, France, UK, Greece, Ireland, Italy, Netherlands, Norway, Portugal, and Sweden. The survey contains information on individual demographics, such as age, gender, education, marital status, employment status, and household size, as well as life satisfaction indicators. In particular, the survey asks "On the whole, are you very satisfied, fairly satisfied, not very satisfied or not at all satisfied with the life you lead?". Answers to this question are available for every year except 1996.

Annual country total advertising expenditure data are available from ZenithOptimedia, which is a global media services company. They publish a quarterly report (the "Advertising Expenditure Forecasts") that covers advertising from a large number of markets around the world. This record contains the total amount spent on advertising in the country historically as well as forecasts for the future. Here historical data are used from 1980 to 2011, as reported in the issue "Advertising Expenditure Forecasts of December 2013." Further details are available in the Advertising Expenditure Forecasts of ZenithOptimedia (Austin et al., 2013).

Macroeconomic indicators are taken from the World Bank. In particular, data are available by country for the years 1980 to 2011 on GDP, GDP per capita, and the national unemployment rate. These are published in World Development Indicators. Information is combined from all three data sources for the same 27 countries and time periods (1980-2011). The final sample-size for the current study consists of a little over 900,000 observations on randomly sampled European citizens. Table 4.1 presents some descriptive statistics of our sample. It can be seen that our respondents are on average above 44 years old and come from a household approximatively 3 persons. There are slightly less men than women in our sample (47% of men, 53% of women). The considered countries appear to be different in term of macroeconomics variable. The lowest unemployement rate from our sample is 2.5% in the Netherlands in 2001 and the highest 24% in Spain in 1994. GDP per capita also vary, going from USD $3,553$ (Bulgaria, 2004) to almost USD $54,600$ (Norway, 1996).

The data are used to estimate coefficients from linear regression models,[5] where

[4]Transition countries are countries whose economies are changing from centrally planned economies into market economies. The classification is made according to the International Monetary Fund (http://www.imf.org/).

[5]Using ordinal or cardinal regressions do not affect the results.

Table 4.1: Descriptive Satistics of our Sample

Variable	Mean	Std. Dev.	Min.	Max.	Observations
Demographics					
Age	44.675	18.161	15	99	1321739
Married	0.612	0.487	0	1	1252627
Male	0.473	0.499	0	1	1353045
Size of the household	2.903	1.491	1	9	1181314
Age Completed Education					
Up to 14	0.214	0.41	0	1	1239393
15-19	0.463	0.499	0	1	1239393
20 or older	0.229	0.42	0	1	1239393
Macroecomics Variables					
Unemployment Rate (%)	8.875	3.818	2.5	23.9	1295463
GDP per Capita [1]	27988	10590	3554	54599	1330368

[1] GDP per capita is measured in 2005 constant USD.

robust clustered standard errors are computed to account for the fact that the errors may be correlated within countries. Life satisfaction scores are regressed on a variety of control variables as detailed below. Specifically, the main equation that is estimated is

$$LS_{ijt} = \alpha + \beta AdvExp_{jt} + \Phi Demo_{ijt} + \Gamma Macro_{jt} + \nu_j + \eta_t + \epsilon_{ijt},$$

where i denotes an individual, j a country, and t a year. The variable LS_{ijt} is reported life satisfaction, $AdvExp_{jt}$ represents advertising expenditures (measured, in turn, as the lag of natural logarithm of total advertising expenditure and as the sum of three previous lags of natural logarithm of total advertising expenditures), the vector $Demo_{ijt}$ contains individual demographic characteristics (age, education, gender, etc.), and $Macro_{jt}$ is a vector of macroeconomic variables that may impact life satisfaction, such as the lag of GDP per capita and the unemployment rate. To control for common country and year attributes, the statistical analysis allows for country ν_j and time η_t fixed effects. The ϵ_{ijt} term captures an individual, country, year specific error. A number of different specifications are estimated as robustness checks.

4.3 Results

Figure 4.1 is an illustration of the study's key idea. The figure divides the data into tertiles and then plots the (uncorrected) relationship between the change in advertising and the change in life satisfaction. The three vertical bars separate the data into countries that over our period of study had particularly large increases in advertising expenditure, moderate increases, and small increases. Figure 4.1 demonstrates that the greater is the rise in advertising, the smaller is the rise in life satisfaction. It is based on our sample of approximately 1 million individuals over the years 1980 to 2011.[6]

Regression analyses reported in Table 4.2 provide evidence of a more formal kind.

[6] Or for shorter periods where full data are not available for a particular country.

Table 4.2: OLS Regressions of Life Satisfaction on Advertising Expenditure (27 countries, 1980- 2011)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Demographics									
Age	-0.022***	-0.022***	-0.022***	-0.022***	-0.022***	-0.022***	-0.022***	-0.022***	-0.022***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age Squared	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployed	-0.382***	-0.385***	-0.385***	-0.385***	-0.385***	-0.385***	-0.386***	-0.386***	-0.385***
	(0.027)	(0.027)	(0.025)	(0.027)	(0.027)	(0.025)	(0.027)	(0.027)	(0.025)
Married	0.170***	0.170***	0.171***	0.170***	0.170***	0.171***	0.170***	0.170***	0.172***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Male	-0.017*	-0.018*	-0.017*	-0.017*	-0.018*	-0.017*	-0.017*	-0.017*	-0.017*
	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)	(0.007)
Size of the Household	0.0046	0.0047	0.005	0.005	0.005	0.005	0.005	0.005	0.005
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age when Completed Education									
Up to 14	-0.227***	-0.227***	-0.229***	-0.227***	-0.227***	-0.229***	-0.226***	-0.226***	-0.229***
	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)	(0.022)
Between 15 and 19	-0.156***	-0.156***	-0.157***	-0.157***	-0.156***	-0.157***	-0.155***	-0.155***	-0.157***
	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)	(0.019)
Older than 20	-0.030*	-0.030*	-0.030*	-0.030*	-0.030*	-0.030*	-0.030*	-0.030*	-0.030*
	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Macroeconomic Variables									
Unemployment Rate in the Country	-0.010*	-0.008	-0.006	-0.010*	-0.008	-0.006	-0.009	-0.006	-0.005
	(0.004)	(0.004)	(0.005)	(0.005)	(0.004)	(0.005)	(0.005)	(0.005)	(0.005)
Log GDP per Capita	0.134	0.234	0.297*	0.398	0.415	0.517*	0.432*	0.388	0.454*
	(0.105)	(0.121)	(0.138)	(0.216)	(0.231)	(0.228)	(0.178)	(0.190)	(0.191)
Log 1^{st} Lag GDP per Capita				-0.278	-0.182	-0.229	-0.087	0.313	0.209
				(0.184)	(0.198)	(0.203)	(0.200)	(0.208)	(0.186)
Log 2^{nd} Lag GDP per Capita							-0.225	-0.431	-0.360
							(0.218)	(0.213)	(0.209)
First Lag of Adv Expenditure									
Log Total Adv Expenditure		-0.069*			-0.067*			-0.085*	
		(0.028)			(0.028)			(0.036)	
Sum of Adv Expenditure (1^{st} to 3^{rd} lags)									
Sum of Log Adv Expenditure			-0.097*			-0.092*			-0.094*
			(0.036)			(0.036)			(0.037)
Fixed Effects									
Year	yes	yes	yes	yes	yes	yes	yes	yes	yes
Country	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	2.177	1.638	1.328	2.327*	1.628	1.372	2.384*	1.422	1.232
	(1.066)	(1.138)	(1.241)	(1.094)	(1.126)	(1.224)	(1.150)	(1.242)	(1.227)
N	760,252	742,497	683,551	742,497	742,497	683,551	717,441	717,441	683,551
adj. R^2	0.214	0.213	0.215	0.213	0.213	0.215	0.213	0.214	0.215

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Clustered (by country) robust standard errors in parentheses. Number of clusters: 27. All regressions include year and country dummies (base line country is Austria). Dependent variable: reported life satisfaction. The exact question is: "On the whole, are you very satisfied, fairly satisfied, not very satisfied or not at all satisfied with the life you lead". The overall mean of the dependent variable is 2.98. Natural logarithm of GDP per capita and lagged advertising expenditures is used. Advertising expenditures are in constant 2005 million USD and GDP per capita in constant 2005 USD.

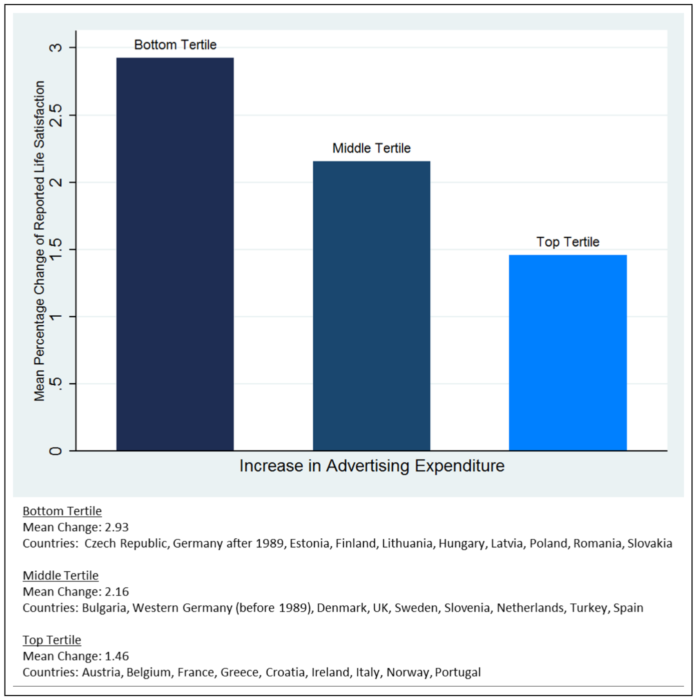

Figure 4.1: Changes in Advertising and Changes in the Life Satisfaction of Countries

They show the same pattern. In column 1 of Table 4.2, the now-standard statistical specification for national happiness equations (see, for example, Di Tella et al., 2001; Di Tella et al., 2003; Radcliff, 2013) fits the data in the conventional way. A variable for the person's age enters with the quadratic form that is commonly found in the well-being literature; being married and highly educated are both associated with greater satisfaction with life; being unemployed is associated with low levels of life satisfaction; the unemployment rate in the country enters negatively; GDP is positive but statistically weak.

Columns 2 to 9 of Table 4.2 reveal links between life-satisfaction scores in the current period with past advertising levels. Table 4.2 shows what happens when advertising variables are included within the regression equation, where columns 4 and 7 give the base results without advertising included. In each case, the advertising variables enter negatively, with small standard errors (this is after adjustment for potential biases from clustering). In column 2, for example, the coefficient on the logarithm of advertising expenditure is -0.069 with a standard error of 0.028. This variable is for advertising lagged one period. In column 3, the coefficient on the stock of advertising (measured as the sum of advertising expenditures over three previous years, again in logarithms) is -0.097 with a standard error of 0.036.

There is a natural potential criticism of the regression equations in the second and third columns of Table 4.2. It is that an advertising variable might in some way be erroneously standing in for earlier business-cycle movements. The later columns of Table 4.2 probe that possibility. In each case, however, the key result is robust. The most general specifications are in columns 8 and 9 of Table 4.2, but even with three GDP per-capita terms included (that is, current GDP and two variables for lagged GDP in each of the two prior years) the advertising variables continue to be statistically significant and of similar size to that in earlier columns. Hence the advertising variables are not creating a spurious association that is attributable merely to the state of the business cycle in any particular year or country.

One feature of Table 4.2 is that the effects from GDP tends to become somewhat larger after the inclusion of the advertising variables (for example, in column 2 compared to column 1). This is consistent with the hypothesis that, although rises in GDP tend to be beneficial, the benefits of economic growth may be somewhat offset by a rise in advertising expenditure. Following the tradition in much of the literature on the economics of advertising (Bain, 1956; Bagwell, 2001), Table 4.2 also uses a variable for the *stock of advertising*. This is designed to capture the idea that commercial organizations spend money on advertising to build up a lasting brand in the minds of their consumers.

It may be useful to emphasize that the results reported here include the following covariates: age, whether unemployed, whether married, whether male, size of family, level of education, the unemployment rate in the country, and GDP-per-capita in the country. Throughout the paper's tables, variables for country dummies and year dummies are included. These covariates are the standard ones in the modern literature on the social science of well-being. However, unlike previous longitudinal studies of national well-being, the data set has the advantage that it allows us to incorporate measures of advertising expenditure for each country and year.

In Table 4.3, which explores a range of lag lengths, the robustness of the original result is evident: rises in advertising are precursors to declines in well-being. The size of the predictive power of advertising on later life-satisfaction depends on the time lag between the two variables. Longer lags, as in the right-hand columns of Table 4.3, are associated with more-negative estimates.

In these tables the estimated advertising effect-size is substantial. For column 3 of Table 4.2, for example, the coefficient on the stock of advertising is -0.097. Because this variable is in logarithms, the percentage change of life satisfaction with respect to the percentage change in (the stock of) advertising is approximately -0.03 (this calculation uses the fact that the mean of life satisfaction is 2.98, which has to be used to divide the number -0.097), and -0.03 can thus be thought of as the long-run elasticity of national well-being with respect to advertising spending. This implies that a hypothetical doubling of advertising expenditure would result in a 3 percent drop in life satisfaction. Around the mean of 2.98, therefore, that would be a fall of 0.09 life satisfaction points when measured on the one to four scale used in the Eurobarometer Surveys. That is considerable. It is approximately one half the absolute size of the marriage effect on life satisfaction, or approximately one quarter of the absolute size of the effect of being unemployed (the coefficient on marriage is 0.17 and that on unemployment is -0.38).

Table 4.4 the summarizes the levels of advertising expenditure for the different nations. On average, countries spend just under 1% of GDP in this way. Table 4.5 presents results for fixed-effects models in which the kind of advertising expenditure

Table 4.3: OLS Regressions of Life Satisfaction on Various Lagged Advertising Expenditure (27 countries, 1980-2011)

	(1)	(2)	(3)	(4)
Demographics				
Age	-0.022***	-0.022***	-0.022***	-0.022***
	(0.001)	(0.001)	(0.001)	(0.001)
Age Squared	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Unemployed	-0.382***	-0.385***	-0.386***	-0.385***
	(0.0278)	(0.027)	(0.027)	(0.025)
Married	0.170***	0.170***	0.170***	0.171***
	(0.008)	(0.008)	(0.008)	(0.008)
Male	-0.017*	-0.018*	-0.017*	-0.017*
	(0.007)	(0.007)	(0.007)	(0.007)
Size of the Household	0.005	0.005	0.005	0.005
	(0.003)	(0.003)	(0.003)	(0.003)
Age when Completed Education				
Up to 14	-0.227***	-0.227***	-0.226***	-0.229***
	(0.022)	(0.022)	(0.022)	(0.022)
Between 15 and 19	-0.156***	-0.156***	-0.155***	-0.157***
	(0.019)	(0.019)	(0.019)	(0.019)
Older than 20	-0.030*	-0.030*	-0.028*	-0.030*
	(0.013)	(0.013)	(0.013)	(0.013)
Macroeconomic Variables				
Log GDP per Capita	0.213	0.234	0.264*	0.296*
	(0.115)	(0.121)	(0.127)	(0.132)
Unemployment Rate in the Country	-0.009*	-0.008	-0.006	-0.005
	(0.004)	(0.004)	(0.004)	(0.005)
Log of Adv Expenditure				
Log Total Adv Expenditure	-0.051			
	(0.029)			
Log 1^{st} Total Adv Expenditure		-0.069*		
		(0.028)		
Log 2^{nd} Lag Total Adv Expenditure			-0.085**	
			(0.028)	
Log 3^{rd} Total Adv Expenditure				-0.094**
				(0.031)
Fixed Effects				
Year	yes	yes	yes	yes
Country	yes	yes	yes	yes
Constant	1.738	1.638	1.485	1.195
	(1.095)	(1.138)	(1.201)	(1.226)
N	760252	742497	717441	683551
adj. R^2	0.214	0.213	0.214	0.215

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Clustered (by country) robust standard errors in parentheses. Number of clusters: 27. All regressions include year and country dummies (base line country is Austria). Dependent variable: reported life satisfaction. The exact question is: "On the whole, are you very satisfied, fairly satisfied, not very satisfied or not at all satisfied with the life you lead". The overall mean of the dependent variable is 2.98. Natural logarithm of GDP per capita and lagged advertising expenditures is used. Advertising expenditures are in constant 2005 million USD and GDP per capita in constant 2005 USD.

Table 4.4: Advertising Expenditure as % of GDP and Per-Capita

Country	Adv Exp as % of GDP	Ad Exp per Capita
Austria	0.822	297.682
Belgium	0.590	191.633
Bulgaria	1.425	63.014
Croatia	2.087	224.648
Czech Republic	0.549	79.078
Germany (after 1989)	0.852	277.089
Denmark	0.804	331.678
Estonia	0.037	4.025
Finland	0.750	253.400
France	0.591	177.633
Greece	0.802	147.355
Hungary	0.746	83.254
Ireland	0.374	126.301
Italy	0.426	191.633
Lithuania	0.446	38.557
Latvia	0.496	38.553
Netherlands	0.737	257.164
Norway	0.454	226.266
Poland	0.585	53.950
Portugal	0.473	80.912
Romania	0.119	6.617
Spain	0.828	178.838
Sweden	0.677	260.986
Slovenia	0.006	1.194
Slovakia	0.849	114.504
Turkey	0.314	23.551
UK	0.911	288.355
Total	0.683	195.003

Table 4.5: OLS Regressions of Life-Satisfaction on Disaggregated Advertising Expenditure (27 countries, 1980-2011)

	(1)	(2)	(3)	(4)
Demographics				
Age	-0.022***	-0.022***	-0.021***	-0.022***
	(0.001)	(0.001)	(0.001)	(0.001)
Age Squared	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)
Unemployed	-0.387***	-0.385***	-0.382***	-0.381***
	(0.025)	(0.025)	(0.024)	(0.024)
Married	0.171***	0.171***	0.178***	0.178***
	(0.008)	(0.008)	(0.008)	(0.008)
Male	-0.017*	-0.017*	-0.017*	-0.017*
	(0.007)	(0.007)	(0.007)	(0.007)
Size of the Household	0.005	0.005	0.005	0.005
	(0.003)	(0.003)	(0.003)	(0.003)
Age when Completed Education				
Up to 14	-0.229***	-0.229***	-0.228***	-0.228***
	(0.022)	(0.022)	(0.024)	(0.024)
Between 15 and 19	-0.157***	-0.157***	-0.159***	-0.159***
	(0.020)	(0.019)	(0.023)	(0.022)
Older than 20	-0.030*	-0.030*	-0.035*	-0.034*
	(0.013)	(0.013)	(0.015)	(0.015)
Macroeconomic Variables				
Log GDP per Capita	0.413***	0.297*	0.409**	0.408
	(0.080)	(0.138)	(0.123)	(0.210)
Country in Transition	0.268	0.133	0.132	0.133
	(0.130)	(0.194)	(0.230)	(0.329)
Unemployment Rate in the Country		-0.006		-0.000
		(0.005)		(0.005)
Stock of Adv Expenditure				
Sum of Log Adv Expenditure	-0.118***	-0.0966*		
	(0.032)	(0.036)		
Sum of Log Newspaper Adv Expenditure			-0.080*	-0.080*
			(0.033)	(0.035)
Sum of Log Magazines Adv Expenditure			-0.053	-0.053
			(0.029)	(0.030)
Sum of Log TV Adv Expenditure			0.051	0.050
			(0.033)	(0.035)
Sum of Log Radio Adv Expenditure			0.003	0.003
			(0.020)	(0.019)
Sum of Log Cinema Adv Expenditure			0.000	0.000
			(0.023)	(0.024)
Fixed Effects				
Year	yes	yes	yes	yes
Country	yes	yes	yes	yes
Constant	0.292	1.328	-0.017	-0.009
	(0.715)	(1.241)	(1.175)	(1.993)
N	686139	683551	572226	569638
adj. R^2	0.215	0.215	0.207	0.208

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Clustered (by country) robust standard errors in parentheses. Number of clusters: 27. All regressions include year and country dummies (base line country is Austria). Dependent variable: reported life satisfaction. The exact question is: "On the whole, are you very satisfied, fairly satisfied, not very satisfied or not at all satisfied with the life you lead". The overall mean of the dependent variable is 2.98. Natural logarithm of GDP per capita and lagged advertising expenditures is used. Advertising expenditures are in constant 2005 million USD and GDP per capita in constant 2005 USD.

Table 4.6: OLS Regressions of Life-Satisfaction for 12 Non-Transitory Countries from 1980 to 1995

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	satis	satis	satis	satis	satis	satis	satis	satis	satis
Demographics									
Age	-0.021***	-0.021***	-0.021***	-0.021***	-0.021***	-0.021***	-0.021***	-0.021***	-0.021***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Age Squared	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***	0.000***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployed	-0.403***	-0.405***	-0.397***	-0.405***	-0.405***	-0.397***	-0.404***	-0.404***	-0.397***
	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)	(0.041)
Married	0.161***	0.161***	0.163***	0.161***	0.161***	0.163***	0.161***	0.161***	0.163***
	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)	(0.011)
Male	-0.025*	-0.025*	-0.023	-0.025*	-0.025*	-0.0231*	-0.024*	-0.024*	-0.023*
	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.011)	(0.010)	(0.010)	(0.011)
Size of the Household	0.002	0.002	0.002	0.002	0.00178	0.002	0.002	0.002	0.002
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Age when Completed Education									
Up to 14	-0.191***	-0.190***	-0.198***	-0.191***	-0.191***	-0.199***	-0.191***	-0.191***	-0.199***
	(0.029)	(0.028)	(0.027)	(0.028)	(0.028)	(0.027)	(0.028)	(0.027)	(0.027)
Between 15 and 19	-0.113***	-0.114***	-0.121***	-0.114***	-0.114***	-0.121***	-0.115***	-0.115***	-0.121***
	(0.024)	(0.023)	(0.024)	(0.023)	(0.023)	(0.024)	(0.023)	(0.023)	(0.024)
Older than 20	-0.025	-0.026	-0.029*	-0.026	-0.026	-0.0286*	-0.025	-0.025	-0.029*
	(0.013)	(0.013)	(0.012)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)	(0.013)
Macroeconomic Variables									
Unemployment Rate in the Country	-0.005	-0.005	-0.005	-0.006	-0.00538	-0.005	-0.005	-0.005	-0.004
	(0.006)	(0.006)	(0.006)	((0.006)	(0.006)	(0.005)	(0.006)	(0.005)	(0.006)
Log GDP per Capita	0.705***	0.680***	0.830**	1.146**	1.086*	1.142*	1.102*	0.978*	0.890*
	(0.168)	(0.152)	(0.209)	(0.335)	(0.372)	(0.489)	(0.386)	(0.384)	(0.410)
Log 1^{st} Lag GDP per Capita				-0.541	-0.449	-0.359	-0.0256	0.214	0.438
				(0.434)	(0.438)	(0.540)	(0.492)	(0.480)	(0.431)
Log 2^{nd} Lag GDP per Capita							-0.446**	-0.560**	-0.592***
							(0.134)	(0.151)	(0.140)
First Lag of Adv Expenditure									
Log Total Adv Expenditure		-0.059			-0.053			-0.070	
		(0.028)			(0.031)			(0.042)	
Sum of Adv Expenditure (1^{st} to 3^{rd} lags)									
Sum of Log Adv Expenditure			-0.028			-0.025			-0.028
			(0.030)			(0.031)			(0.035)
Fixed Effects									
Year	yes	yes	yes	yes	yes	yes	yes	yes	yes
Country	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	-3.618	-2.984	-4.619*	-2.607	-2.583	-4.162	-2.800	-2.354	-3.672
	(1.704)	(1.528)	(2.120)	(2.208)	(1.810)	(2.460)	(2.637)	(2.133)	(2.703)
N	319796	313985	278594	313985	313985	278594	300709	300709	278594
adj. R^2	0.164	0.163	0.166	0.163	0.163	0.166	0.164	0.164	0.166

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Clustered (by country) robust standard errors in parentheses. Number of clusters: 12. All regressions include year and country dummies (base line country is Belgium). Dependent variable: reported life satisfaction. The exact question is: "On the whole, are you very satisfied, fairly satisfied, not very satisfied or not at all satisfied with the life you lead". The overall mean of the dependent variable is 3.04. Natural logarithm of GDP per capita and lagged advertising expenditures is used. Advertising expenditures are in constant 2005 million USD and GDP per capita in constant 2005 USD.

Table 4.7: OLS Regressions of Life-Satisfaction for 14 Non-Transitory Countries from 1996 to 2011

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
	satis	satis	satis	satis	satis	satis	satis	satis	satis
Demographics									
Age	-0.019***	-0.019***	-0.019***	-0.019***	-0.019***	-0.019***	-0.019***	-0.019***	-0.019***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Age Squared	0.000***	0.000***	0.00***	0.00***	0.00***	0.000***	0.000***	0.000***	0.000***
	(0.0000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Unemployed	-0.388***	-0.388***	-0.388***	-0.388***	-0.388***	-0.388***	-0.388***	-0.388***	-0.388***
	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)	(0.042)
Married	0.181***	0.181***	0.182***	0.181***	0.182***	0.182***	0.181***	0.182***	0.182***
	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)	(0.012)
Male	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010	-0.010
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Size of the Household	0.010*	0.010*	0.010*	0.010*	0.010*	0.010*	0.010*	0.010*	0.010*
	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
Age when Completed Education									
Up to 14	-0.254***	-0.254***	-0.254***	-0.254***	-0.254***	-0.254***	-0.254***	-0.254***	-0.254***
	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)	(0.031)
Between 15 and 19	-0.143***	-0.143***	-0.143***	-0.143***	-0.143***	-0.143***	-0.143***	-0.143***	-0.143***
	(0.024)	(0.024)	(0.024)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)	(0.023)
Older than 20	-0.028	-0.028	-0.028	-0.027	-0.027	-0.0277	-0.027	-0.027	-0.028
	(0.016)	(0.016)	(0.016)	(0.016)	(0.015)	(0.015)	(0.016)	(0.015)	(0.015)
Macroeconomic Variables									
Unemployment Rate in the Country	-0.008	-0.008	-0.006	-0.006	-0.006	-0.006	-0.006	-0.006	-0.006
	(0.006)	(0.006)	(0.006)	(0.006)	(0.006)	(0.007)	(0.007)	(0.007)	(0.007)
Log GDP per Capita	0.341	0.469	0.547	0.871	0.859	0.775	0.776	0.786	0.774
	(0.435)	(0.489)	(0.449)	(0.566)	(0.569)	(0.555)	(0.480)	(0.481)	(0.472)
Log 1st Lag GDP per Capita				-0.548	-0.465	-0.269	-0.192	-0.198	-0.265
				(0.695)	(0.811)	(0.811)	(0.608)	(0.598)	(0.582)
Log 2nd Lag GDP per Capita							-0.256	-0.205	-0.003
							(0.388)	(0.439)	(0.526)
First Lag of Adv Expenditure									
Log Total Adv Expenditure		-0.062			-0.033			-0.026	
		(0.104)			(0.116)			(0.121)	
Sum of Adv Expenditure (1^{st} to 3^{rd} lags)									
Sum of Log Adv Expenditure			-0.115			-0.097			-0.097
			(0.119)			(0.132)			(0.145)
Fixed Effects									
Year	yes	yes	yes	yes	yes	yes	yes	yes	yes
Country	yes	yes	yes	yes	yes	yes	yes	yes	yes
Constant	-0.082	-0.940	-1.243	0.078	-0.411	-0.982	0.020	-0.352	-0.981
	(4.563)	(4.767)	(4.339)	(4.818)	(5.526)	(4.986)	(4.817)	(5.569)	(5.044)
N	280362	280362	280362	280362	280362	280362	280362	280362	280362
adj. R^2	0.221	0.221	0.221	0.221	0.221	0.221	0.221	0.221	0.221

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Clustered (by country) robust standard errors in parentheses. Number of clusters: 14. All regressions include year and country dummies (base line country is Austria). Dependent variable: reported life satisfaction. The exact question is: "On the whole, are you very satisfied, fairly satisfied, not very satisfied or not at all satisfied with the life you lead". The overall mean of the dependent variable is 3.07. Natural logarithm of GDP per capita and lagged advertising expenditures is used. Advertising expenditures are in constant 2005 million USD and GDP per capita in constant 2005 USD.

Table 4.8: Reverse Causality - Log Total-Advertising Expenditure

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Advertising Last Period								
Log of Total Adv Exp Last Period	0.824***	0.813***	0.943***	0.944***	0.966***	0.941***	0.940***	0.941***
	(0.077)	(0.072)	(0.017)	(0.013)	(0.017)	(0.015)	(0.016)	(0.013)
Macroeconomic Variables								
Unemployment Rate in the Country	-0.006	-0.005	-0.009**	-0.008**	-0.009*	-0.00741**	-0.00786**	-0.00749***
	(0.004)	(0.004)	(0.002)	(0.002)	(0.003)	(0.002)	(0.002)	(0.002)
Log GDP per Capita	1.865***	1.879***	1.833***	1.833***	1.764***	1.788***	1.771***	1.766***
	(0.258)	(0.268)	(0.258)	(0.274)	(0.270)	(0.284)	(0.280)	(0.292)
Log 1^{st} Lag GDP per Capita	-1.637***	-1.610***	-1.820***	-1.809***	-1.713***	-1.543***	-1.550***	-1.497***
	(0.314)	(0.310)	(0.272)	(0.275)	(0.368)	(0.375)	(0.377)	(0.374)
Log 2^{nd} Lag GDP per Capita					-0.120	-0.235	-0.202	-0.242
					(0.198)	(0.193)	(0.196)	(0.218)
Mean Satisfaction								
Current Mean Satisfaction	-0.018				0.038			
	(0.105)				(0.075)			
1^{st} Lag Mean Satisfaction		0.013				-0.002		
		(0.067)				(0.042)		
2^{nd} Lag Mean Satisfaction			-0.043				-0.037	
			(0.055)				(0.056)	
3^{rd} Lag Mean Satisfaction				0.040				0.054
				(0.053)				(0.052)
Fixed Effects								
Year	yes	yes	yes	yes	yes	yes	yes	yes
Country	yes	yes	yes	yes	yes	yes	yes	yes
Constant	-0.968	-1.392	0.520	0.169	0.950	0.424	0.459	0.103
	(1.539)	(1.267)	(0.866)	(0.749)	(1.394)	(0.955)	(0.877)	(0.767)
N	438	435	412	389	416	416	412	389
adj. R^2	0.997	0.997	0.998	0.998	0.999	0.998	0.998	0.998

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$. Clustered (by country) robust standard errors in parentheses. Number of clusters: 27. All regressions include year and country dummies (base line country is Austria). Dependent variable: log of total advertising expenditure (in constant 2005 million USD). Mean satisfaction is the average of reported life satisfaction by year and country. GDP is per capita in constant 2005 USD.

is disaggregated into five different categories (newspapers, magazines, TV, radio, and cinema).It is the first two kinds that exhibit large and significant negatives. Tables 4.6 and 4.7 show that, dividing the data period into two halves for the non-transition countries, the coefficient on advertising is fairly stable across time. This is a check on robustness. Importantly, all twelve of the coefficients, across the two tables, are negative. In Table 4.6 the advertising coefficient is approximately -0.06, and in Table 4.7 it averages to a similar size (though is somewhat smaller for lagged advertising and bigger for the stock of advertising). Standard errors, of course, are inevitably larger than for the full sample of thirty years taken as a whole; the appropriate test is instead for stability in coefficient sizes.

We also check, in the spirit of Granger-causality tests (Granger, 1969), for possible reverse linkages. Table 4.8 reveals no evidence that lagged values of life satisfaction have predictive power in an advertising equation.

4.4 Conclusion

This paper has explored a long-debated question in social science: how is the well-being of a nation affected by advertising? It is the first empirical study of its kind. The paper's results are consistent with conceptual concerns expressed more than a century ago by authors such as Veblen (1904) and Robinson (1933); they are potentially consistent with arguments made in later writings such as by Easterlin (2003) and Layard (1980); they may also be consistent with ideas about the deleterious consequences of materialism (Sirgy et al., 2012; Burroughs and Rindfleisch, 2002; Speck and Roy, 2008; Snyder and Debono, 1985). Rises and falls in advertising expenditure in Europe's nations have been shown here to be followed by falls and rises in life-satisfaction levels. There is evidence for a longitudinal relationship between national advertising and national dissatisfaction. The estimated effect-size is substantial and not merely statistically well-determined.

Acknowledgment

Thanks to the participants of the Zurich Workshop on Economics 2015 for their comments. Information on how to obtain the Eurobarometer data is available on the European Commission website http://ec.europa.eu/public_opinion/index_en.htm.

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